Safety Assessment of New England Roadways During the COVID-19 Pandemic

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About the Transportation Infrastructure Durability Center

The Transportation Infrastructure Durability Center (TIDC) is the 2018 US DOT Region 1 (New England) University Transportation Center (UTC) located at the University of Maine Advanced Structures and Composites Center. TIDC's research focuses on efforts to improve the durability and extend the life of transportation infrastructure in New England and beyond through an integrated collaboration of universities, state DOTs, and industry. The TIDC is comprised of six New England universities, the University of Maine (lead), the University of Connecticut, the University of Massachusetts Lowell, the University of Rhode Island, the University of Vermont, and Western New England University.

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16 Abstract

Safety assessment of roadway facilities is a critical task to maintain the system operational efficiency of transportation infrastructure. The comprehensive stay-at-home orders implemented in response to the COVID-19 pandemic have resulted in massive reductions in traffic volumes, especially on major highways. Motorists have responded to these greatly reduced volumes by increasing their travel speeds; the result of this behavioral response has been an increase in the rate and incidence of fatal crashes. There is a clear need to analyze speeding during and after the duration of stay-at-home orders. In addition, the rate of severe injury and fatal crashes continued to remain high in 2021 and 2022, even when the traffic volume returned to the pre-pandemic condition. This project employed an innovative approach to use traditional data archived from permanent count stations, as well as new data sources (i.e., probe data) to develop models to better understand the impact of pandemic on New England roadways. Particularly, this research developed models to analyze speeding during and after COVID-19 stay-at-home orders in Maine and Connecticut. This research also developed models to better understand the impact of pandemic on crashes in 2021, and 2022, and explore if any factors other than speed, also impacted the increase in rate of severe and fatal crashes in years after the stay-at-home order in Maine.

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Abstract

The COVID-19 pandemic caused a significant change in traffic operations and safety. For instance, various U.S. states reported an increase in the rate of fatal and severe injury crashes over this duration. In April and May 2020, comprehensive stay-at-home orders were issued across the country including Maine and Connecticut. These orders resulted in drastic reductions in traffic volume. Additionally, there is anecdotal evidence that speed enforcement had been reduced during pandemic. Drivers responded to these changes by increasing their speed. More importantly, data show that speeding continued to occur, even one year after the onset of the pandemic. There is a clear need to analyze speeding during and after the duration of the stay-at-home orders. In addition, the rate of severe injury and fatal crashes continued to remain high in 2021 and 2022, even when the traffic volume returned to the pre-pandemic condition. Several research studies modeled crash occurrence and severity during the stay-at-home orders, but limited research has been devoted to exploring crash data in 2021 and 2022, after travel restrictions were lifted, to examine the long-term effect of the pandemic.

This study first develops statistical models to quantify the impact of the pandemic on speeding in Maine. Models are developed for three rural facility types (i.e., major collectors, minor arterials, and principal arterials) using a mixed effect Binomial regression model and short duration speed and traffic count data collected at continuous count stations in Maine. Our results show that the odds of speeding by more than 15 mph increased by 34% for rural major collectors, 32% for rural minor arterials, and 51% for rural principal arterials (non-Interstates) during the stay-at-home order in April and May of 2020 compared to the same months in 2019. In addition, the odds of speeding by more than 15 mph, in April and May of 2021, one year after the order, were still 27% higher on rural major collectors and 17% higher on rural principal arterials compared to the same months in 2019.

Second, this study uses a mixed effect binomial regression model to investigate the impact of the stay-at-home order on odds of speeding on urban limited access highway segments in Maine and Connecticut. This study also establishes a link between traffic density (vehicles per mile) and the odds of speeding. For this purpose, hourly speed and volume probe data were collected on limited access highway segments for the U.S. states of Maine and Connecticut to estimate the traffic density. The traffic density then was combined with the roadway geometric characteristics, speed limit, as well as dummy variables denoting the time of the week, time of the day, and COVID-19 phases (before, during and after stay-at-home order), and the interactions between them. Density, represented in the model as Level of Service, was found to be associated with the odds of speeding, with better levels of service such as A, or B (low density) resulting in the higher odds that drivers would speed. We also found that narrower shoulder width could result in lower odds of speeding. Furthermore, we found that during the stay-at-home order, the odds of speeding by more than 10, 15, and 20 mph increased respectively by 54%, 71% and 85% in Connecticut, and by 15%, 36%, and 65% in Maine during evening peak hours. Additionally, one year after the onset of the pandemic, during evening peak hours, the odds of speeding greater than 10, 15, and 20 mph were still 35%, 29%, and 19% greater in Connecticut and 35% 35% and 20% greater in Maine compared to before pandemic.

Third, using probe data, this study analyzes four years of hourly traffic volume and operating speed information on homogenous segments of urban and rural limited access highway segments in Maine. This information then combined with roadway characteristics and two dummy variables signifying the years of 2021 and 2022 to develop short duration models using logistic

regression for both urban and rural areas and different times of the week and day. Incorporating the operational speed variables in the models, the models explore if any factors, other than speed, also contributed to the increase in total and/or fatal-injury crashes in 2021 and 2022. We found that while the change in operating speed explains the increase in crashes in some situations, indeed, the effect is beyond that in other conditions. For instance, for urban roadways, the odds of fatal and injurious crash occurrence increased by 87% in 2021 for evening peak hours and by 79% for off-peak hours compared to the pre-restriction period (2018-19). Furthermore, decreased odds of a crash during morning peak hours were observed, representing a temporal shift in crash occurrence. Additionally, the coefficient of variation (CV) of hourly speed was found to be significant and positively associated with crash occurrence for nearly all models.

Chapter 1: Introduction

Upon the onset of the COVID-19 pandemic, various states across the United States (U.S.) issued stay-at-home orders. The unprecedented orders in turn caused a tremendous reduction in vehicle trips, and consequently the volume of traffic on roads; at the same time, roadway fatality rates increased across the country (Doucette et al., 2021; Stiles et al., 2021; Adanu et al., 2021; Dong et al., 2022). For instance, in Connecticut, despite 43% reduction in Vehicle Miles Traveled (VMT), the rate of fatal single vehicle crashes increased by 4.1 times in the early stages of the pandemic (Doucette et al., 2021). Initially, it was hypothesized that the increase in fatality rate and crash severity occurred mainly due to increased speeding on roadways with lower volumes and less enforcement during the stay-at-home orders (Stiles et al., 2021; Dong et al., 2022). However, data from National Highway Traffic Safety Administration (NHTSA) show that the fatal crash rates were still elevated throughout 2021 and even into 2022 (Wang and Cicchino, 2023; National Center for Statistics and Analysis, 2022). Due to the prevalence of speeding as a factor in severe accidents during the-stay at-home period, and the continued elevated rate of fatal crash outcomes, it is necessary to study how speeding behavior changed both during and after travel restrictions were lifted.

Speeding is a contributing factor in many fatal and serious injury crashes (Cooper, 1997; Elvik, 2005; Abegaz et al., 2014; Adanu et al., 2021; Wang, and Cicchino, 2023). Researchers found that several factors impact speeding, including but not limited to roadway geometry and functional class (Afghari et al., 2018; Eluru et al., 2013), posted speed limit (Yokoo et al., 2019), time of day, time of week and holidays (Jun, 2010; Heydari et al., 2020), light conditions (De Bellis et al., 2018), vehicle classification (Afghari et al., 2018), weather conditions (Kurte et al., 2019), enforcement (Hauer et al., 1982; Tay, 2005), and driver psychology or perceived risk (Tucker et al., 2021). Enforcement, particularly, can have a profound impact on reducing the average speed on roadways. Hauer et al. (1982) reported the reduction of speed to a number around the speed limit upstream and downstream of sites with parked police cars; they also found that the speed reduction could continue near enforcement sites for several days, even after the removal of the police cars. Similar observations were also reported in Norway, where police cars were left on segments of roadway with 60 and 80 km/h speed limits for an average of 9 hours per day over a period of 6 weeks. This was found to result in significant speed reduction, even after the vehicles were removed (Vaa et al., 1997). Researchers also found that speeding reduces with the implementation of speed cameras. For instance, Afghari et al. (2018) found that a 1% increase in speed cameras would correlate to about a 3.5% reduction in speeding.

The occurrence of speeding can be identified using observed vehicle speeds and speed limits. The methodology by which speed is collected, however, has evolved over time. Camera and inductive loop detectors at count stations have been and still are used by many states. This method provides volume and sometimes speed data at fixed locations but fails to capture effects across a network. As most drivers are now carrying cell phones, companies such as StreetLight[1], can capture Location-Based Services (LBS) and Global Positioning System (GPS) data from these devices to provide speed and volume data across all segments of a roadway network (Turner et al., 2017; Yang et al., 2020). The availability of these probe data has enabled the effect of traffic stream variables to be captured across the entire network, as opposed to just a handful of permanent count

[1]StreetLight applies proprietary big data processing resources and machine-learning algorithms to measure travel patterns of vehicles, bicycles, and pedestrians, and makes them available on-demand via its SaaS platform, StreetLight InSight®.

stations or across a specific arterial. Several existing studies have used probe data. Yokoo et al., 2019 used speed data collected from GPS to determine that a greater percentage of drivers exceed the speed limit at speed limits below 25 mph and over 55 mph, or at night. Kurte et al. (2019) used vehicle probe data from the city of Chicago to examine how weather events cause variations in traffic speed across the roadway network, showing how drivers slow down in response to poor weather conditions. Cai et al. (2021) used Inrix probe data to evaluate speed reduction strategies. In Connecticut, Doucette et al. (2020) used Streetlight's LBS based probe data to estimate VMT in the state before and during the COVID-19 stay-at-home order. These VMT estimates were then used with crash data to determine how the crash rates among different crash types changed with the reduction in traffic volume caused by the order.

Speed, flow, and density are three major traffic stream parameters playing crucial roles in establishing various design standards or evaluating roadway safety. According to traffic flow theory, these three parameters are interrelated; an increase or decrease in one will impact the others (Mannering, and Washburn, 2020). Although the impact of traffic flow or volume on speeding has been studied significantly, limited research has been done regarding the impact of traffic density. This is partially due to gaps in data collection and the difficulty of observing density. Density, however, can have a crucial impact on speed or speeding. In fact, the Level of Service (LOS) of basic freeway segments, which is a qualitative measure on freedom to maneuver or speed, is directly associated with the level of density on the roadway segments. With probe data technology, it is possible to find space mean speed and traffic volume on roadway segments and consequently calculate the density. We use such data to establish the relationship between speeding and different levels of density.

This study, first, aims to understand the impact of the COVID-19 pandemic (e.g., reduction in enforcement or change in perceived risk) on speeding during the stay-at-home order (April and May 2020), and one year after stay-at-home order (April and May 2021) on rural roads in Maine. In this study, short-term traffic count and speed data from Maine roadways were used. The data were collected every 5 minutes at 23 continuous count stations operated by Maine Department of Transportation (MaineDOT) located on rural major collectors, minor arterials, and non-Interstate principal arterials. A mixed effect Binominal model with logit link function was developed to model speeding as a function of traffic count, accounting for factors such as time of the day, day of the week, and month of the year, and the speed limit. Two dummy variables were included to denote the duration of the stay-at-home order implementation (April and May 2020), and one year after the onset of pandemic (April and May 2021) to understand if other factors other than traffic volume reduction impacted the increased speeding trend.

Second, this study explores the change in odds of speeding on urban limited access highways (Interstates and freeways) during and after stay-at-home orders imposed in Maine (ME) and Connecticut (CT). The information about speeding and traffic density was derived from probe data provided by StreetLight Insight®. We then used a mixed effect binomial model to establish a link between the odds of speeding and contributing factors denoting the traffic density, roadway geometric characteristics, speed limit, time-related factors, two dummy variables signifying the duration of the stay-at-home order and one year since lifting the order, and several interaction variables. This section of research contributes to literature in multiple ways. First, we demonstrate the application of probe data (using hourly traffic volume and speed data from StreetLight Insight®) to analyze the odds of speeding. To the best of our knowledge, limited research, if any, has been devoted to model odds of speeding using hourly probe data. Second, unlike previous studies, we study speeding for the entire network divided into homogenous segments, instead of fixed locations or a specific arterial, taking advantage of the availability of network-level probe data. Third, using data from homogenous segments, we can include different roadway characteristics in the model, allowing us to measure the effect of variables such as presence of the curve and shoulder width on odds of speeding. Fourth, we establish a link between traffic density or level of service and speeding. To our knowledge, there is also limited research on this topic due to inherent difficulties in estimating the density. However, using the hourly probe data, we can obtain detailed density information, and establish a link between level of service and speeding. Fifth, and most importantly, we investigate how the odds of speeding changed during the stay-at-home order and one year since the onset of the pandemic on urban limited access highways in Maine and Connecticut, especially in morning and evening peak hours. Finally, we explore if there are any differences in odds of speeding between Maine and Connecticut.

Third, this study contributes to literature by modeling the effect of operational speed on crash occurrence after pandemic closures. Generally, models that relate operating speed to crash occurrence are challenging to estimate and studied less frequently than other models in transportation safety literature. The models estimated in this study will help to identify variables that influence the crash occurrence in new conditions which have emerged since the COVID-19 pandemic closures. We leverage emerging probe data to perform a network level analysis of the crash occurrence. Previous studies mainly relied on speed data collected at permanent count stations or a specific arterial, rather than an entire network. Accessing the hourly probe data along all controlled access highway segments in the study area, all these segments could be incorporated in the model. In addition, by utilizing data through the end of 2022 in our analysis, we are using data to model very recent conditions. Few if any reviewed papers have published analysis performed using data so recent in their analysis of emerging conditions following the COVID-19. This current study aims to address this gap in research by modeling total and fatal-injury crash occurrence using short duration models.

Chapter 2: Literature Review

This chapter provides a comprehensive review[2] of studies related to Transportation Safety and COVID-19 pandemic. As a result of the COVID-19 pandemic and subsequent travel restrictions, traffic patterns on roadways have undergone a significant change. Many cities, states and countries around the world issued travel guidelines (e.g., stay-at-home orders) to contain the spread of the COVID-19 pandemic, resulting in drastic changes in transportation demand and services; such drastic changes created new transportation challenges, obstacles, and problems. Among these challenges, transportation safety has been significantly affected since the onset of the COVID-19 pandemic. During the travel restrictions, various cities, states, and countries reported an increase in the rate of severe-injury and fatal crashes as well as more frequent risky driving behavior. While initially thought to be a temporary condition, the increase in severe crashes or risky behavior persisted and/or evolved even long after the travel restrictions were removed (National Center for Statistics and Analysis, 2022; Wang and Cicchino, 2023; Marshall, et al., 2023). In addition, both transit and pedestrian and bicycle (ped/bike) safety were also affected by the COVID-19 pandemic. Transit services were affected mainly due to reduced services and required social distancing among users (Kapatsila et al., 2022; Kapatsila & Grise, 2021; Salama & McGarvey, 2022). The safety of ped/bikes were affected mainly due to the increased presence of these users on facilities not well designed to accommodate their higher volumes (Christie, 2021; N. Dong et al., 2022; Gouda et al., 2021; Monfort et al., 2021; Redelmeier & Zipursky, 2021).

Researchers across the world have employed different types of data, methods, and analyses to address unique challenges transportation safety encountered during the COVID-19 pandemic. They aim to determine how transportation safety has changed and/or evolved during different phases of the pandemic and the public health responses to it. Using a structured critical review, we outline research studies conducted regarding transportation safety in the wake of the pandemic. Primarily, we divide the review into three major sections: roadway, transit, and ped/bike safety. For roadway safety, two major subcategories are discussed; first, we discuss direct measures such as the impact of COVID-19 on crashes, then, the indirect (or surrogate) measures of safety such as risky behaviors (e.g., speeding) are discussed. In each section, we highlight the safety challenges, and findings across the U.S., as well as other countries. When possible, we cover studies conducted in different phases of pandemic. We also review data and methods used for analysis. Following the review, the key findings are summarized, research gaps are discussed, and suggestions for future research are formulated. Table 1 shows the reviewed studies based on the study subject, location of the study, data and method used for analysis, and key findings. This chapter reviews the existing literature on COVID-19 and transportation safety.

2.1. Roadway Safety

Roadway safety was substantially impacted by the COVID-19 pandemic. This includes an increase in crash severity (e.g., more fatal crashes) and risky behaviors (e.g., more speeding). This section is divided into two major parts. First, we cover studies related to direct safety measures (i.e., crash data and models); then, studies related to indirect safety measures (e.g., speeding) are documented and discussed.

[2] The literature review section was updated from the start of the project to also reflect the latest research related to the COVID-19 pandemic and Transportation Safety. Therefore, the papers published based on the results of the current report (Chapter 3 and 4) by Shahlaee et al. (2022), and Marshall et al. (2023) also were partially included, referenced, and discussed in this section for the sake of completeness of the literature review.

Table 1 List of papers reviewed and Key Findings.

Subject	Authors (Year)	Title	Location	Data/Method	Key Findings
Road	Abraham et al. (2021)	Elevated wildlife-vehicle collision rates during the COVID-19 pandemic	United States	Crash Reports/Explanatory Statistics	Although roadway traffic decreased by more than 7% with a maximum decrease of 40%, there was no change in the number of wildlife incidents leading to an 8% increase in crashes, peaking at 27%
Road	Adanu et al. (2021)	How did the COVID-19 pandemic affect road crashes and crash outcomes in Alabama?	United States	Crash Reports, VMT/Modelling severity	Major injury probability was increased by .0007 in aggressive driving crashes and by .023 in the case of no-seatbelt crashes. The probability of major crash injuries on interstates increased by more than .047 after the onset of the pandemic
Road	Adanu et al. (2022)	Understanding the Factors Associated with the Temporal Variability in Crash Severity before, during, and after the COVID-19 Shelter-in-Place Order	United States	Crash Reports, VMT/Injury Severity Models with Heterogeneity in Means	Prior to shelter-in-place, 2.6% of crashes resulted in major injury. This increased to 3.7% during travel restrictions and 3.8% after. Travel restrictions had minimal effect on DUI, speeding, distracted, and fatigued driving crashes, but did have increase in aggressive driving crashes.
Road	Alhajyaseen et al. (2022)	Road safety status during COVID-19 pandemic: Exploring public and road safety expert's opinions	Qatar	Survey Data/Explanatory Statistics	Traffic crashes were reduced by 70% but rate of severe and fatal crashes increased by 140% and 111% respectively during peak periods. 33% of safety experts disagreed that roads had become safer and 55% disagreed that driving had improved. Overall, 70% of experts were found to have said that the pandemic had a significant effect on roadway safety.
Road	Amberber et al. (2021)	Road Traffic Injury During the COVID-19 Pandemic: Cured or a Continued Threat?	Toronto, Canada	Toronto Traffic and Crash Data/ Explanatory Statistics	Increase in vehicle speeds during travel restriction period. Toronto police reported 35% increase in speeding citations and 200% increase in stunt driving indicating rise in risky behavior
Road	Arun Pathac et al. (2022)	Analysis of Motor Vehicle Accidents: Comparison Between Before and During the COVID-19 Lockdown in Maharashtra, India	India	Crash Reports/ Explanatory Statistics	During the travel restriction period, the number of crashes was reduced by 88.6%, with the number of crashes increasing with each subsequent phase of "reopening". Through crashes reduced by about 85% the ratio of fatal crashes increased by 1.27 times. Fatal crashes increased the most in days 40-54 from the initial order.
Road	Barnes et al. (2021)	COVID-19 lockdown and traffic accidents: Lessons from the pandemic	United States	Crash Reports, Google Mobility Data/Regression Discontinuity in Time	Observed a 47% reduction in crashes, with a 41% reduction in crashes involving an ambulance. Conditional on an ambulance being involved, the likelihood of a fatal crash increased from 2.2 to 3.8%. Drivers aged 25-64 experienced smaller relative decline in crash involvement, presumably due to presence in essential workforce.

Road	Chand et al. (2021)	A Descriptive Analysis on the Impact of COVID-19 Lockdowns on Road Traffic Incidents in Sydney, Australia	Australia	Crash Reports/Explanatory Statistics	Sydney experienced two travel restriction periods. During the first, a 30% decrease in fatalities was observed with a 50% reduction in overall accidents. During the second, fatalities decreased 53% and overall crashes by 64% compared to previous years. Crashes decreased with the proportion of crashes to drivers not changing significantly.
Road	Das et al. (2022)	Did Operating Speeds During COVID-19 Result in More Fatal and Injury Crashes on Urban Freeways?	United States	Roadway Data, HERE Traffic Data, Crash Data/Safety Prediction Models	Found increase in speeding and increase in severe accidents with decrease in volume. Modelled speeding and found that it was positively associated with severe and fatal outcome during the COVID period.
Road	Das & Sarkar (2022)	News Media Mining to Explore Speed-Crash-Traffic Association During COVID-19	Global	News Articles/Text Mining	Media reported increased fatal crashes, inattentive driving, DUI, reduced enforcement, equity, and ped/bike changes, often noted by local, U.S., and international news.
Road	Dong, X et al. (2022)	How did COVID-19 impact driving behaviors and crash Severity? A multigroup structural equation modeling	United States	Crash Data/ Structural Equation Modelling	Higher likelihood of severe crashes taking place on highways. Increased association of aggressive or inattentive driving with crash severity after pandemic.
Road	Doucette et al. (2021)	Initial impact of COVID-19's stay-at-home order on motor vehicle traffic and crash patterns in Connecticut: an interrupted time series analysis	United States	Probe Data, Crash Reports/Explanatory Statistics	43% reduction in state VMT after onset of travel restrictions. Single vehicle crashes increased 2.29 times with single vehicle fatal rates increasing by 4.1 times. Incidence rate of multiple vehicle crashes decreased overall, however did not decrease for fatal crashes
Road	Garner et al. (2023)	Predictors of risky driving among teen drivers with ADHD during U.S. COVID-19 shelter in place orders	United States	Used simulator eye tracking data and vehicle event monitoring data	Found that some teens with ADHD, specifically ones with oppositional defiant disorder/conduct disorder, were at an increased likelihood of engaging in risky driving behavior during the pandemic.
Road	Gong et al., (2023)	Impact of COVID-19 on traffic safety from the "Lockdown" to the "New Normal": A case study of Utah	United States	Crash and Mobility Data/Negative Binomial and Binary Logit	Lower crash frequency during the pandemic but increasing as restrictions are reduced. Crash severity increased during the early pandemic, due to speed, DUI, commercial vehicles, and reduced seat belt use.
Road	Gupta et al. (2021)	Impact of lockdown and change in mobility patterns on road fatalities during COVID-19 pandemic	Various	Crash Data, Lockdown Stringency, Mobility, Country Specific Details/Generalized Linear Mixed Model with clusters	Found change in fatalities given change in a type of mobility; for example, a 10% decrease in work-related trips was found to be associated with only a 3.1% and 7.1% decrease in fatal accidents for the two clusters respectively. The study also showed that countries with stricter travel restrictions and better

					compliance also suffered a less drastic decrease in traffic safety.
Road	Inada et al. (2021)	COVID-19 lockdown and fatal motor vehicle collisions due to speed-related traffic violations in Japan: a time-series study	Japan	Crash Reports/Forecasting and comparison to historic data	The observed rate of fatal motor vehicle collisions was above the forecasted rate's 95% confidence interval only for the month of April 2020
Road	Islam, M et al. (2023)	Evidence of sample selectivity in highway injury-severity models: The case of risky driving during COVID-19	United States	Survey Data, Crash Reports/Random Effects Multinomial Logit Modelling	Survey data showed that more vehicle miles were travelled by riskier drivers; however, modelling data found that increased severities was due to behavior at large, rather than the greater proportion of riskier drivers.
Road	Islam, S. et al. (2023)	Impacts of COVID-19 Pandemic Lockdown on Road Safety in Bangladesh	Bangladesh	Crash Reports/ Seasonal Autoregressive Integrated Moving Average Model	Found that crashes overall were down, but that rates of collisions and fatal collisions were elevated during restriction period.
Road	Kazatras et al. (2020)	A descriptive analysis of the effect of the COVID-19 pandemic on driving behavior and road safety	Greece, Saudi Arabia	Probe Driver Data, Apple Mobility/ Explanatory Statistics	6-11% increase in speeds, a 12% increase in harsh braking incidents, and a 42% increase in phone use while driving. Crashes in Greece dropped by 41% and about 80% during morning hours.
Road	Lin et al. (2021)	Assessing inequality, irregularity, and severity regarding road traffic safety during COVID-19	United States	Crash Reports/Mobility Change Point, Regression, spatial analysis	Spatial shift in crash locations from wealthier to less wealthy areas in studied cities. Increase in proportion of those involved in crashes that were either "Hispanic" or "male", increasing by about 5% in the case of male
Road	Marshall et al. (2023)	Leveraging Probe Data to Model Speeding on Limited Access Highway Segments During the COVID-19 Pandemic	United States	Probe Data/Mixed Effect Binomial Regression	The odds of speeding by more than 10, 15, and 20 mph increased respectively by 54%, 71% and 85% in Connecticut, and by 15%, 36%, and 65% in Maine during evening peak hours. Increase in odds of speeding continues into 2021, after lifting of travel restrictions. Link established between operational performance and odds of speeding indicates that better roadway performance is associated with increased odds of speeding.

Road	National Center for Statistics and Analysis. (2021);(2022)	Early Estimate of Motor Vehicle Traffic Fatalities in 2020; Early Estimates of Motor Vehicle Traffic Fatalities And Fatality Rate by Sub-Categories in 2021	United States	Crash and VMT Data/Explanatory Statistics	Two reports showing how crash rates changed in 2020 and 2021. In 2020, the fatal crash rate increased from 1.11 fatalities per one-hundred-million miles to 1.37. In 2021 the nationwide rate had decreased slightly to 1.34 fatalities per one-hundred-million miles.
Road	Paramasivan et al. (2022)	Impact of COVID-19 pandemic on road safety in Tamil Nadu, India	India	Crash Reports/Explanatory Statistics	Found 74%, 81%, and 75% reductions in fatal, serious, and minor incident crashes respectively.
Road	Patwary & Khattak (2023)	Crash harm before and during the COVID-19 pandemic: Evidence for spatial heterogeneity in Tennessee	United States	Crash and Socioeconomic Data/Poisson, Geographically Weighted Regression, Generalized Least Squares Regression	Found that while total crashes decreased by 15.3%, fatal crashes increased by 8.2% following the onset of the COVID-19 Pandemic. Modelling showed that fatal crashes that occurred during the pandemic were more associated with speeding and reckless driving, dark roadways, and commercial vehicles.
Road	Rapoport et al. (2021)	Impact of COVID-19 on motor vehicle injuries and fatalities in older adults in Ontario, Canada	Canada	Crash Reports/Explanatory Statistics	Found that drivers 80 and older reduced by 64.7% for crash involvement, while drivers 35-54 reduced by only about 23%.
Road	Rudisill (2021)	The association between a statewide stay-at-home order and motor vehicle injury rates among population sub-groups in West Virginia	United States	CDC Data, Population Data, VMT Data	Found that there was a decrease in driving, with the decrease being greater for younger and older drivers, as opposed to those aged 26-45. Also found that there was a greater decrease in miles travelled for female drivers versus male drivers.
Road	Saladie et al. (2020)	COVID-19 lockdown and reduction of traffic accidents in Tarragona province, Spain	Spain	Crash Reports/Spatial analysis, Explanatory Statistics	Found a decrease of 62.9% in overall mobility in early 2020. Compared to the preceding months in 2020, accidents in March and April of 2020 fell by 74.3%, and compared with the same dates in 2018 and 2019, they fell by 76%
Road	Sedain et al. (2021)	Road traffic injuries in Nepal during COVID-19 lockdown.	Nepal	Crash Reports, Media Reports/Explanatory Statistics	Ratio of deaths to injuries in traffic incidents went from 1:46.3 to 1:20.6 during the travel restriction period
Road	Sekadakis et al. (2021)	Analysis of the impact of COVID-19 on collisions, fatalities and injuries using time series forecasting: The case of Greece	Greece	Crash Reports, COVID Cases, Apple Mobility/Time Series Model, Forecasting	Identified an increase in fatality rate of 3% in March, 28% in April, and 37% in May

Road	Shahlaee et al. (2022)	Modeling the Impact of the COVID-19 Pandemic on Speeding at Rural Roadway Facilities in Maine using Short-Term Speed and Traffic Count Data	United States	Count Data/Mixed Effect Logistic Regression	The odds of speeding by 15 mph or more on major collectors, rural major collectors, rural minor arterials, and rural principal arterials increased by 34%, 32%, and 51% respectively. These odds remained 21% higher on rural major collectors and 17% higher on rural principal arterials one year after travel restrictions were lifted. Greatest increase in odds of speeding during evening peak hours
Road	Stavrinos et al. (2020)	Adolescent driving behavior before and during restrictions related to COVID-19	United States	Driver behavior data	Found that overall, studied drivers (aged 16-18) reduced the number of days in which they drove by 37% and the distance they drove by 35% during the pandemic.
Road	Stiles et al. (2021)	Lower Volumes, Higher Speeds: Changes to Crash Type, Timing, and Severity on Urban Roads from COVID-19 Stay-at Home Policies	United States	Crash Reports, Network and Speed Data/MNL model of volume to severity. Bayesian hierarchical logistic regression of Speed to severity	More than doubled odds of incapacitating or fatal crash during the travel restriction period. The probability of a crash being fatal increased from .26% to .42% during the travel restriction period
Road	Tucker et al. (2021)	Speeding through the pandemic: Perceptual and psychological factors associated with speeding during the COVID-19 stay-at-home period	N/A	Review of Historical Psychological Studies w/ Extrapolation	Drivers base their speed of their environment largely, observing the environment around them rather than their own speedometer. Furthermore, fewer vehicles for drivers to pay attention to leads the under stimulation and driver fatigue.
Road	Vandoros et al. (2021)	Empty Streets, Speeding and Motor Vehicle Collisions during Covid-19 Lockdowns: Evidence from Northern Ireland	Northern Ireland	Crash Reports, Citation Records/Interrupted Time Series Analysis	During the first travel restriction period there was a reduction in injuries of 42%, 32% for serious injuries, and there was no significant change in the number of fatalities
Road	Wang & Cicchino (2023)	Changes in speeding on Virginia roads during the beginning of the COVID-19 pandemic	United States	Continuous Count Data/Logistic Regression	Risk of speeding 5 and 10 mph increased by 22% and 51% respectively. Additionally, the number of vehicles speeding was highest during peak hours on weekdays and afternoons on weekends.
Road	Watson-Brown et al. (2021)	Drink driving during the COVID-19 pandemic	Australia	Survey Data	During pandemic, random roadside breath testing was suspended in Queensland. This was found to make drivers who had previously driven drunk more likely to drive drunk, and increased the likelihood for some drivers who had not previously driven drunk.

Road, Transit, Bicycle	Wegman & Katrakazas (2021)	Did the COVID-19 pandemic influence traffic fatalities in 2020? A presentation of first findings	Worldwide	Fatality and modal miles travelled data	Found that overall fatality rates decreased by 3%, but in April 2020 increased by 33%. Found the greatest decrease in fatalities on transit due to sharp ridership decline. Found the least reduction in fatalities for bicycles due to increased usage. Found 8% increase in bike fatalities in The Netherlands despite a 16% reduction in bike kilometers travelled.
Transit	Kapatsila et al. (2021)	Public Transit Riders' Perceptions and Experience of Safety: COVID-19 Lessons from Edmonton	Canada	Survey Data/Explanatory Statistics	Riders perceived a higher risk of transmission of COVID-19 when riding transit. A percentage of riders had switched to commuting by car. Riders who had returned to transit were those who were of low-means groups of who were less susceptible to the virus.
Transit	Kapatsila et al. (2022)	From Riding to Driving: The Effects of the COVID-19 Pandemic on Public Transit in Metro Vancouver	Canada	Survey Data/Explanatory Statistics	Riders perceived a higher risk of transmission of COVID-19 when riding transit. A percentage of riders had switched to commuting by car. Riders who had returned to transit were those who were of low-means groups of who were less susceptible to the virus.
Transit	Katt (2022)	Perception of Safety on Transit During COVID-19: A Case Study of Berlin, Germany	Germany	Survey Data/Explanatory Statistics	Found that transit agency's efforts to promote their hygienic responses to the pandemic had little effect of rider's decisions to return to transit.
Transit	Ozbilen et al. (2021)	Perceived risk of infection while traveling during the COVID-19 pandemic: Insights from Columbus, OH	United States	Survey Data/Explanatory Statistics	Riders perceived a higher risk of transmission of COVID-19 when riding transit. A percentage of riders had switched to commuting by car. Riders who had returned to transit were those who were of low-means groups of who were less susceptible to the virus.
Transit	Salama et al. (2022)	Enhancing mass transit passenger safety during a pandemic via in-vehicle time minimization	N/A	Formulation of MILP to minimize in-vehicle time	Simulated skip stop transit service to estimate in-vehicle time savings using MILP. Simulations involved transit lines up to 50 stops in length. It was found that an average in-vehicle reduction time of 34% could be achieved, with up to 24% being achieved while keeping 90% or more of trips direct.
Bicycle, Road	Christie (2022)	Pandemic and recovery: What are the implications for road safety?	Britain	Literature Review	Found evidence of growth in non-driving transportations as well as increase in road hazards such as bike delivery where riders may be under pressure to ride quickly.

Bicycle, Pedestrian, Road	Dong, N et al. (2022)	Association of human mobility with road crashes for pandemic-ready safer mobility: A New York City case study	United States	Crash Reports/Explanatory Statistics	New York City motorist fatalities increased by more than 70% while motorist injuries decreased 20.8% during the travel restriction period. Fatalities increased despite nearly 80% decrease in crashes overall.
Bicycle	Buehler et al. (2021)	COVID-19 Impacts on Cycling	Europe, Americas, Australia	Crash Reports/Explanatory Statistics	EU averaged 8% bicycle growth while U.S. averaged 16%. Most of this growth was concentrated on weekends as opposed to weekdays
Bicycle	Monfort et al. (2021)	Weekday bicycle traffic and crash rates during the COVID-19 pandemic	United States	Bicycle Count Data/Explanatory Statistics	Fatal and injury bike crash rates found during 2013-2019 were compared with those of 2020. Researchers found reduction of 28% in bicyclists fatal and injurious crashes, presumably due to reduction in traffic volume, or due the shift in using multi-use pathways instead of roadway commuting bike routes.
Bicycle	Yan et al. (2021)	Quantifying the impact of COVID-19 on e-bike safety in China via multi-output and clustering-based regression models	China	Crash Reports, Economic Data, Weather/	Areas with higher pre-pandemic percentage of incidences experienced significant decrease in the number of e-bike crashes, while areas with lower pre-pandemic incidences areas experience smaller reductions in e-bike crashes regardless of the urban or rural population, presumably due to increase in online shopping, replacing the need for in-person shopping.
Pedestiran, Road	Gouda et al. (2021)	Effect of Redesigning Public Shared Space Amid the COVID-19 Pandemic on Physical Distancing and Traffic Safety	Canada	CCTV footage, Machine Vision/Explanatory Statistics	Studied the effect of narrowing roadways to allow for more pedestrian space. Decreased speeds of between 4.2 and 10.5 km/h in study areas, but increased jaywalking by 11.9% to 34.6%
Pedestrian	Redelmeier et al. (2021)	Pedestrian Deaths During the COVID-19 Pandemic.	North America	Crash Reports, Mobility Data/Regression Modelling	The number of fatal pedestrian crashes in New York and Toronto was reduced at first, but eventually returned to normal. In the early pandemic, the rate of pedestrian fatality increased, suggesting that there are other unobserved factors affecting the likelihood of pedestrian crashes than just the pedestrian volumes

2.1.1 Direct Measures of Roadway Safety

Crash reports are the primary source of data used for safety analyses and evaluations. In this section, first, crash statistics and key observations since the start of the pandemic are reviewed; then, the crash models developed to understand the contributing factors for the increase in occurrence and severity of crashes are discussed.

Crash Statistics

Upon the start of the pandemic, countries around the world issued guidelines to their citizens to reduce their daily trips. These guidelines took various forms, with some places like U.S. states issuing stay-at-home orders that mainly involved restrictions on public places and gathering, as well as travel guidelines within and outside of states; in some other countries, there were stricter policies and restrictions, even to the point that drivers had to receive permission to use their vehicles (see Sedain & Pant, 2021). We use the term "travel restrictions" to refer to all kinds of orders and restrictions. We also use "stay-at-home orders" when we refer to orders and guidelines released in the early stages of the pandemic by U.S. states. In response to these travel restrictions, travel patterns were disrupted, travel demand for most daily trips (e.g., to workplaces and schools) decreased, and the traffic volume on roadways drastically reduced.

It is widely known that the crash occurrence is directly associated with traffic volume; generally, higher traffic volume is associated with more crash observations. However, while a few places reported a decrease in the rate of total crashes (see Saladié et al., 2020), most cities, states, and countries around the world found an increase in severe-injury and fatal crash rates when travel restrictions were in place, in spite of drastic reduction in traffic volume (Adanu et al., 2022, 2021; Arun Pathak et al., 2022; Barnes et al., 2021; Das et al., 2022; Das and Sarkar, 2022; Dong et al., 2022; Doucette et al., 2021; Gong et al., 2023; S. Islam et al., 2023; Paramasivan and Sudarsanam, 2022; Patwary & Khattak, 2023; Sedain and Pant, 2021; Vandoros and Papailias, 2021; Wang et al., 2023, Wegman & Katrakazas, 2021). The phenomenon was apparent to the public during this period, as news media highlighted more crashes, elevated rates of risky behavior, and the effects of more bikes and pedestrians on roads (Das & Sarkar, 2022).

In the United States, crash statistics showed an increase in single and multi-vehicle fatal crashes (Doucette et al., 2021), crashes that required ambulance transport (Barnes et al., 2021), and collisions with animals (Abraham & Mumma, 2021). The increase in crashes suggested a change in driving behavior and more risky driving on roads, such as increased aggressive driving, reduced seatbelt usage, inattentiveness, and speeding (Adanu et al., 2021, 2022; Amberber et al., 2021; Das et al., 2022; Dong et al., 2022; Islam et al., 2023; Patwary & Khattak, 2023). The increased risk taking is supported by the difference found in the fatality rate for single and multi-vehicle crashes during the pandemic. For instance, a study in Connecticut, U.S., showed 2.3 and 4.1 times increase in the rate of total and fatal single vehicle crashes. This study also showed that the rate of fatal multi-vehicle crashes increased by 8% during the stay-at-home order (Doucette et al., 2021).

The demographics of drivers involved in crashes changed during the travel restrictions in early stages of the pandemic (Adanu et al., 2021; Lin et al., 2021; Rapoport et al., 2021; Rudisill, 2021). A study conducted using New York and Los Angeles data showed that crash rates increased in lower-income neighborhoods and among male and Hispanic drivers (Lin et al., 2021). In addition, age played a role in crash involvement; for example, drivers with over 80 years of age were involved in 64% fewer crashes compared to the pre-pandemic level, while drivers aged 35-

54 were involved in only 23% fewer crashes (Rapoport et al., 2021). Studies also showed that drivers with an age of 65 or more were involved in more multi-vehicle crashes during the period of the stay-at-home order than before pandemic (Adanu et al., 2021). Stavrinos et al. (2020) reported that traffic fatalities decreased for the age groups of below 18 years old and over 75 (Wegman & Katrakazas, 2021). The age disparities are likely due to essential workers belonging to a young to middle age group, while juvenile drivers (less than 18 years old) had less trip demand as schools had closed; elderly drivers were less likely to go out for risk of COVID exposure. A recent study, however, showed an increased likelihood of risky behavior in some teens who have Attention-Deficit Hyperactivity Disorder (ADHD), following the onset of the pandemic (Garner et al., 2023).

Severe crash outcomes did not just become more prevalent in the United States. In India, Greece, and Ireland, as well, the rate of severe injury and fatal crashes increased (Arun Pathak et al., 2022; Sekadakis et al., 2021; Vandoros & Papailias, 2021). The ratio of severe crashes to all crashes also increased in Australia, India, and Nepal (Chand et al., 2021; Paramasivan & Sudarsanam, 2022; Sedain & Pant, 2021). Similar to the United States, there was evidence of increased risk taking (e.g., more speeding) in Ireland, Japan, and Greece (Inada et al., 2021; Katrakazas et al., 2020; Vandoros & Papailias, 2021) as well as other risky behaviors such as increased cell phone use in some regions (Katrakazas et al., 2020). In India, the rate of injuries per crash increased by 28.4% while the fatal crash rate increased by 1.27 times (Arun Pathak et al., 2022).

Australia uniquely experienced two separate major travel restriction periods, allowing a comparison between an initial and subsequent travel restrictions (Chand et al., 2021). In the first restriction, only essential trips such as grocery shopping, work, and education (if unable to be done remotely) were allowed. The second restriction was more stringent and limited citizens to travel first within a 10 km radius, and later within 5 km radius from their residences. Local governmental areas were sometimes used to delineate where residents could and could not go. Furthermore, during this phase, even in-person jobs like construction, considered "essential" by other restrictions, were halted for two weeks. During the first travel restriction, a 50% reduction in overall crash frequency, and a 30% decrease in fatalities were observed compared to the previous year. During the second restriction, fatalities decreased by 53% compared to the previous year, while crashes overall were 64% less frequent. This analysis was conducted using the comparison of crash frequency ratios year over year, and did not consider any exposure (e.g., vehicle miles travelled or traffic volume) data (Chand et al., 2021). Therefore, it is not possible to understand if the change in crash patterns is due to a change in exposure or not.

Though travel restrictions have now been lifted and volumes have returned back to pre-pandemic levels, there is still evidence of a disruption to traffic safety (Marshall et al., 2023; Wang & Cicchino, 2023). In the U.S., nationwide statistics showed that, the fatal crash rate increased from 1.11 fatalities per one-hundred-million miles to 1.37 in 2020 (NHTSA, 2021). Statistics published by the same agency showed that in 2021 the nationwide rate had decreased slightly to 1.34 fatalities per one-hundred-million miles (NHTSA, 2022). This shows that despite a "return to normal", the number of crashes is still high and roadway safety issues introduced by the pandemic persist.

Crash Models

Crash occurrence and severity models provide an opportunity to identify the crash trends and find contributing and causal factors for crashes. While descriptive crash statistics compare crash counts (e.g., severe injury and fatal crashes) to exposure, showing that roadway safety was compromised since the start of pandemic, statistical models can examine more detailed factors. This allows them to better quantify the impact of independent variables on crashes. For example, researchers used data from Louisiana collected during the state's stay-at-home order to analyze the frequency of different crash severities (Barnes et al., 2021). They found that conditional on an ambulance being involved, the likelihood of a fatal crash increased from 2.2 to 3.8%.

Another study used a time series model and found that while the number of crashes had been reduced, the ratio of serious to all crashes increased. Furthermore, it was observed that following a return to pre-pandemic traffic conditions, the relative frequencies of different crash severities remained as they were under COVID-19 travel restrictions (Paramasivan & Sudarsanam, 2022). To determine if there was a change in speeding related crashes during the travel restriction period in Japan, the number of crashes of each severity with and without speeding as a contributing factor were forecast from 10 years of historic data and compared to the actual number of crashes (Inada et al., 2021). The model indicated a higher prevalence of speeding related crashes during the pandemic compared to what was expected (Inada et al., 2021). Likewise, a time series model was developed on 10 years of data in Greece to forecast expected crash numbers in 2020 (Sekadakis et al., 2021). The study found a disproportionate decrease in crashes compared to the mobility reduction. The researchers found only a 42% decrease in crashes despite a 56.5% decrease in traffic. Focusing specifically on wildlife collisions, in 2020, traffic in the U.S. reduced by 7 to 40 percent depending on the month, however, the number of wildlife collisions remained unchanged compared to previous years. This indicates at least an 8% increase in the rate of these incidents, with the rate varying by state (Abraham & Mumma, 2021). Using data from Tennessee, several types of models, including Poisson and Geographically Weighted Regression models, were developed to show how crash severity was effected (Patwary & Khattak, 2023). This analysis found that fatal crashes during the pandemic were associated with speeding, reckless driving, dark lighting conditions, and commercial vehicles.

Beyond changes in the rates and ratios of different crash outcomes, researchers also explored variables that influenced crash severity outcomes. Crash outcomes can be affected by different driver, vehicle, roadway, and environmental variables. Multinomial logit and logit models were used by multiple studies to analyze crash severity (Adanu et al., 2021, 2022; Stiles et al., 2021). In Alabama, the multinomial logit model as well as random parameters with heterogeneity in mean and variances was used to examine what variables affected crash severity outcomes (Adanu et al., 2021). Modelling single and multi-vehicle crashes before and after the pandemic separately, the study found that speeding, driving under the influence (DUI), and time of the week (i.e., weekends) accounted for the increased rate of major injury crashes. A similar analysis conducted on data from the U.S. state of Ohio, using multinomial logit modelling to relate daily volume to crash severity and a Bayesian logistic regression to relate increased speed to increased crash severity (Stiles et al., 2021). Speeding was associated with an increase in probability of severe crashes by a factor of 1.21 for every 1 mph of speed. This study also examined the likelihood of fatal crashes for different facility types and found that the occurrence of fatal crashes are more likely on highways, interstates, and local roads than major collectors and principal arterials (Stiles et al., 2021). Likewise, dividing the crashes into highway and non-highway crashes, Dong et al. (2022) found that more severe crashes were likely to take place on highways, rather than non-highways in Virginia. Furthermore, these researchers found that inattentiveness and aggressive driving were the two key contributing factors in increased crash severity following the onset of the pandemic.

A generalized mixed linear model was developed with data from fifteen countries, separated into two clusters to compare different travel restriction responses and the effect of mobility patterns on crashes (Gupta et al., 2021). Countries from North America, South America, Europe, Asia, and Oceania were included in the model. Clustering was performed based on similarities between the country’s' characteristics, such as population age and volume of freight transport. The results showed that a 10% decrease in work-related trips is associated with only a 3.1% and 7.1% decrease in fatal crashes for the two analyzed clusters. Furthermore, the study showed that countries with stricter travel restrictions and better compliance of these restrictions suffered a less drastic decrease in traffic safety.

Researchers also examined how crash outcomes were affected following the end of the travel restrictions (e.g., stay-at-home orders) (Adanu et al., 2022). Using data from Alabama, a random parameters logit model was applied to three different datasets from 2020 representing conditions before, during, and after the stay-at-home order. These models revealed that throughout the entire year, fatigue, speeding, and failure to wear a seatbelt were prime variables affecting the severe injury outcomes (Adanu et al., 2022). Stiles et al. (2021) used multinomial logit modelling to develop models for crash occurrence; they also developed a Bayesian hierarchical logistic regression model to explore how increased average speed affected the likelihood of fatal crash outcome. They found that the average speed may not be a contributing factor to the occurrence of a crash, but it may contribute to causing a fatal outcome.

2.1.2 Indirect Measures of Roadway Safety

Surrogate safety measures are indirect ways of quantifying safety on roadways, playing a complementary role to direct measures (e.g., crash numbers) for safety assessment. These measures include but are not limited to speeding, seatbelt usage, intoxication, the number of police citations or traffic violations; all these variables are correlated with more severe crashes (Abegaz et al., 2014; Cooper, 1997; Hauer et al., 1982; Elvik, 2005). The reviewed studies show a significant shift in driving behavior of roadway users since the onset of pandemic. In Alabama, U.S., researchers found speeding and intoxicated driving to be two significant contributing factors that caused the increase in number of the crashes after pandemic (Adanu et al., 2021); Speeding, driver distraction, and aggressive driving also increased in other states in the U.S., such as Virginia (Wang & Cicchino, 2023), Maine (Shahlaee, et al., 2022; Marshall, et. al., 2023), Texas (Das et al., 2022), and Connecticut (Tucker and Marsh, 2021; Marshall, et al., 2023). These risky behaviors are not limited to the U.S. Researchers in Ireland and Japan also reported higher incidences of speed related collisions during the COVID-19 pandemic (Inada et al., 2021; Vandoros & Papailias, 2021). In the following, we first review studies related to increase in speeding; then, we briefly review studies related to other indirect safety measures.

Speeding

Exceeding the posted speed limit is a major contributing factor to the frequency and severity of crashes. Speeding is often directly associated with an increase of frequency and severity of crashes. Increase in speed (or speeding, to be exact) could increase the safety risk. Multiple factors can influence the operational speed or speeding (see Afghari et al., 2018; de Bellis et al., 2018; Eluru et al., 2013; Heydari et al., 2020; Kurte et al., 2019; Yokoo & Levinson, 2019). Traffic volume and enforcement are possibly the two most important factors impacting the rate of speed violations (Afghari et al., 2018; Hauer et al., 1982). During the COVID-19 travel restrictions, traffic volume reduced drastically; enforcement also reduced substantially in most places. Drivers responded to the new conditions by increasing their speed (Das et al., 2022; Shahlaee, et al., 2022; Wang and Cicchino, 2023; Marshall, et al., 2023). In Texas, researchers found that average speed and the variation in speed were positively associated with severe crash outcomes including fatalities (Das et al., 2022). Furthermore, speeding continued to happen even after travel restrictions were eased or lifted (see Shahlaee et al., 2022; Marshall et al., 2023).

Speeding and general risk taking were also studied through the psychological and environmental factors that contribute to a driver's speed choice. Tucker and Marsh (2021) found that it is likely that drivers are typically regulating their speeds based on visual factors and perceived risk; with fewer cars on the road during the stay-at-home orders, the risk perception could change. Furthermore, it was postulated that the lack of traffic on the roadways also resulted in overall boredom amongst drivers, leading to observed increases in both speeding and distracted driving. When drivers engage in riskier driving behavior or turn their attention to a device in the car, it exposes them to a greater chance of being involved in a crash (Tucker & Marsh, 2021).

Studies from outside of the U.S. also found speeding to have changed during the pandemic. In Northern Ireland, a greater number of speeding citations were issued during the travel restriction period compared to prior to the pandemic (Vandoros & Papailias, 2021). Similarly, Toronto Police observed a 35% increase in speeding citations being issued during March of 2020 compared to before (Amberber et al., 2021). As a contributing factor, speeding was found to be associated with severe-injury and fatal crashes after the beginning of the pandemic in number of studies (Adanu et al., 2021; Arun Pathak et al., 2022; Sedain & Pant, 2021; Vandoros & Papailias, 2021).

Risk Taking, Aggressive Driving, and Intoxication

Several studies also examined risk taking since the onset of stay-at-home orders. Risk taking was found to be more prevalent during the pandemic. For example, an almost 200% increase in stunt driving, which can include excessive speeding, engaging in driving contests, and intentionally causing tires to lose traction, was reported in Toronto, Canada (Amberber et al., 2021). Additionally, as previously mentioned, using the Virginia data, researchers found that aggressive and inattentive driving were associated with increased crash severity (Dong et al., 2022). Using a survey analysis conducted in the United States and Canada, researchers examined how the perceived driving behavior changed between the two countries after pandemic (Vanlaar et al., 2021). This study used self-reported data from surveys of drivers on their risky driving behavior to explore if similar attributes were present. While it was found that speeding was the most common type of risk taken by the citizens of both countries, the second most common factor was impaired driving in the United States, and distracted driving in Canada. Logistic regression was used to examine what factors influenced drivers' responses. The results show that the dummy variable representing the country was a significant factor (Vanlaar et al., 2021), indicating the difference in perceived risk by drivers in the U.S, and Canada.

Stephens et al. (2022) conducted a five-year survey of drivers, collecting self-assessed data on aggressive driving and perceived aggressive driving of others. Surveys were administered five years apart; the second round of surveys happened after the onset of COVID-19 pandemic and included questions on whether the drivers believed the pandemic had affected their driving and others' driving. The study found that most drivers believe that aggressive driving was exacerbated during the COVID-19 travel restrictions period. Specifically, 33% of respondents believed their own aggressive driving and 61% others' aggressive driving increased during pandemic. On the other hand, some researchers found that drivers may perceive that roads are safer following the pandemic even though they are not. A survey study conducted in Qatar showed that drivers perceived the roadways to be safer compared to pre-pandemic, while safety experts believed the opposite (Alhajyaseen et al., 2022). This is possibly because most drivers perceive other drivers to be more dangerous than themselves and when they observed fewer other drivers on the roads, they felt safer. Using a survey analysis in Florida, Islam et al. (2023) found that risky driving was more common among a greater proportion of drivers. These researchers used a random parameters multinomial logit model to conclude that the increased injury severity rate is due to a larger behavioral change rather than a change in the type of drivers on the road (Islam et al., 2023).

Driving under the influence (DUI) of drugs and/or alcohol can greatly impair a driver's ability to react to situations and control their motor vehicle safely. Reviewing crash reports, multiple studies found that DUI happened more frequently during the pandemic than before. For example, in Alabama and Ohio, the proportion of crashes associated with intoxicated driving increased (Adanu et al., 2021; Stiles et al., 2021). Data from Greece and the Kingdom of Saudi Arabia were used to perform a descriptive analysis (Katrakazas et al., 2020) on risk taking. This analysis used probe and Apple mobility data to examine risky activities such as phone use and hard braking. The researchers showed an increase in phone use and harsh braking events during the first two months of the pandemic (Katrakazas et al., 2020). Using Data from Utah, researchers found that increased crash severity was related to DUIs, speeding, and failure to use seatbelts (Gong et al., 2023). A survey study was distributed in Australia to determine how the suspension of random roadside breath testing affected drivers' decisions to drink and drive. It was found that the decreased risk of penalties did increase the likelihood of drivers to drink and drive, particularly in those who had previously engaged in the practice (Watson-Brown et al., 2021).

2.2. Pedestrian and Bicycle Safety

During the pandemic, more people started to use alternative methods of transportation, such as walking and cycling (Buehler & Pucher, 2021; Christie, 2021; Wegman & Katrakazas, 2021). Because of the increased number of pedestrian and bike users, and importance of social distancing due to pandemic, often substantial change was necessary to accommodate these modes. In fact, in some urban areas, sidewalks were widened into roadways to make more room for pedestrians as vehicle traffic was down (Christie, 2021; Gouda et al., 2021). With extra ped/bike volume, however, there was also more exposure for ped/bike users to be involved in crashes. Wegman & Katrakazas (2021) found that worldwide bicycle fatalities had only decreased by 6.4% during the pandemic, owing to increased bicycle usage. They also found that in the bicycle centric country of The Netherlands, there was actually an increase of 8% in cyclist fatalities, despite a 16% reduciton in bicycle kilometers travelled (Wegman & Katrakazas, 2021). In this section, we review how the ped/bike safety evolved since the start of the pandemic.

To better understand the impact of pandemic on ped/bike safety, several researchers examined how pedestrian fatalities had changed in major metropolitan areas such as New York and Toronto. For instance, Redelmeier & Zipursky (2021) used Apple Mobility data collected in 2020 to gather pedestrian and road mobility data to examine the rate of fatal crashes and evaluate the state of vision zero. The study found that, during the initial period of the pandemic, the number of fatal pedestrian crashes in New York and Toronto reduced, but gradually returned to the baseline established from data in past three years. Furthermore, in the early stages of pandemic, although the number of pedestrian fatalities decreased, this reduction was not in proportion to the change in pedestrian exposure. In fact, the rate of pedestrian fatalities increased during the later stages of pandemic, suggesting that there are other, unobserved factors affecting the likelihood of pedestrian crashes than just the pedestrian volume.

Using information from ped/bike crashes, mobility (ped/bike exposure), employment, weather, and travel data, Dong et al. (2022) developed models to better understand the contributing factors in increasing the rate of ped/bike fatalities in New York. The study found an increase in rate of crashes related to shopping trips, supposedly since it is harder to complete an entire shopping trip as a pedestrian or cyclist. These researchers found that unemployment affected the number of ped/bike crashes. They also found that pedestrian crashes were associated with the weather condition. Particularly, when visibility was high, and weather was good, walking and cycling increased, which led to higher crash involvement. In contrast, however, Monfort et al. (2021) reported a reduced crash rate during the pandemic. In Arlington, Virginia, U.S., exposure data were collected using count stations located on on-road bike lanes or off-road bike trailways. Then, fatal/injury bicycle crash rates during 2013-2019 were compared with those of 2020. Researchers found a reduction of 28% in bicyclists fatal/injury crashes, presumably due to reduction in roadway traffic volume, or due the shift in using multi-use pathways instead of commuting bike routes.

In China, e-bikes are of growing prevalence, and their safety was studied in the wake of the pandemic. Yan & Zhu (2021) used cluster models to evaluate e-bike safety across different provinces of China. E-bike accident statistics, socioeconomic data, and COVID-19 case rate data were combined to form a uniform dataset and develop several cluster models. Modeling results showed that areas with a higher pre-pandemic percentage of incidences experienced a significant decrease in the number of e-bike crashes. Meanwhile, areas with lower pre-pandemic incidence rates experienced smaller reductions in e-bike crashes regardless of the urban or rural population. This was presumably due to the increase in online shopping replacing in-person shopping.

Researchers evaluated how redesigning public spaces, such as taking lanes of urban roadways out of service to give pedestrians more space, impacted pedestrian safety (Gouda et al., 2021). This study used mounted cameras and machine vision over two areas in Edmonton, Canada, where traffic lanes had been blocked off for pedestrians. The speed limit adherence and the rate at which pedestrians crossed the street in the middle of blocks were evaluated. It was found that overall this change in design did not adversely impact safety as speed limits were well observed and the number of pedestrians that crossed the street mid-block did not significantly increase (Gouda et al., 2021).

2.3. Transit Safety

Due to COVID-19 social distancing orders, transit ridership was sharply curbed (Christie, 2021; Kapatsila et al., 2022; Kapatsila & Grise, 2021; Katt, 2022; Wegman & Katrakazas, 2021). Much of the body of work produced on transit's reaction to the pandemic is related to ridership and how mode choice has been affected, rather than safety. One exception to this, Wegman and Katrakazas (2021) collected data from 24 countries and found that transit fatalities had decreased by over 64% during the pandemic period, more than any other modes, but largely due to a sharp decline in ridership. Because of the airborne nature of the disease, and the proximity to crowds putting riders at risk, transit safety studies looked to address rider safety in the confined spaces and minimizing the time that riders spent exposed to potential risks. This could also be used to redeem confidence in the safety of transit, as riders perceptions of risk affected their mode choice (Kapatsila & Grise, 2021; Ozbilen et al., 2021)

Studies focusing on rider perceptions of safety were the prevalent form of analysis regarding transit safety (Kapatsila et al., 2022; Kapatsila & Grise, 2021; Katt, 2022; Ozbilen et al., 2021). These studies distributed surveys to city residents to determine what modes they used, why they used them, and what might cause them to return to transit in terms of additional safety measures in cities like Columbus, Ohio, U.S., and Berlin, Germany as well as the cities of Edmonton and Vancouver in Canada. These studies all returned similar results, that is the riders perceived a higher risk of transmission of COVID-19 when riding transit. A percentage of riders had switched to commuting by car. The study conducted in Berlin also found that transit agency's efforts to make public transport vehicles safer and more hygienic had little effect on rider's decisions to return to transit.

One opportunity to increase the safety of transit in the wake of the COVID-19 pandemic was to limit the amount of time that riders spend in any given vehicle. This reduced viral exposure and consequently the likelihood of viral transmission. One such method of reducing the person-in-vehicle time was a transit operation strategy called “skip stop” (Salama & McGarvey, 2022). A study was conducted on this idea to develop an optimization framework which showed the effect of this strategy, where each transit vehicle skips stops to cover distances faster, while other vehicles go to the skipped stops. Transfer stops allow riders to change vehicles to reach stops which would otherwise be skipped. The problem was modelled as a mixed integer linear program (MILP). The objective function was set to minimize time in vehicles with some decision variables added to track in vehicle time and passenger transfers. This MILP was run to simulate several scenarios and determine the effectiveness that a skip stop system could provide in minimizing in-vehicle time. The simulations involved transit lines up to 50 stops in length. It was found that an average in-vehicle reduction time of 34% could be achieved (Salama & McGarvey, 2022).

2.4. Summary and Conclusions

A large body of research has been produced on transportation safety since the beginning of the COVID-19 pandemic. Much of the research focused during this period related to roadway safety. This was particularly relevant as a decrease in safety and an increase in severe crashes was observed on roadways worldwide since the start of pandemic. Studies show, even, that roadway safety has still not returned to where it was pre-pandemic in many parts of the world. Increased risky driving is still observed and accident severities remain elevated. At the same time, transit systems faced new challenges in keeping riders safe, and convincing them to return to riding after the pandemic began to wane. Cycling and walking became more popular, and cities responded to this increased demand by adding bike lanes or widening sidewalks, in some cases permanently.

Chapter 3: Speeding on Rural Roads

This chapter[3] contributes to the current literature by modeling the traffic speeding on rural facilities during the COVID-19 pandemic, using 5-min aggregated data collected at count stations during the comprehensive stay at home order and one year since its inception. We will answer if other factors other than the drastic reduction in traffic volume also influenced speeding during the stay-at-home order, and to what degree the speeding behavior continued to happen approximately one year after the onset of the pandemic compared to before pandemic.

3.1. Data Description

More than 80% of the roads in Maine are rural. Maine DOT has collected 5-minute traffic count and speed data at 23 active continuous count stations on rural roadways in Maine. These 23 stations are located on three different rural facility types. There are 10 stations on rural major collectors, 6 stations on rural minor arterials and 7 stations on rural non-interstate principal arterials. Figure 1 shows the location of the stations.

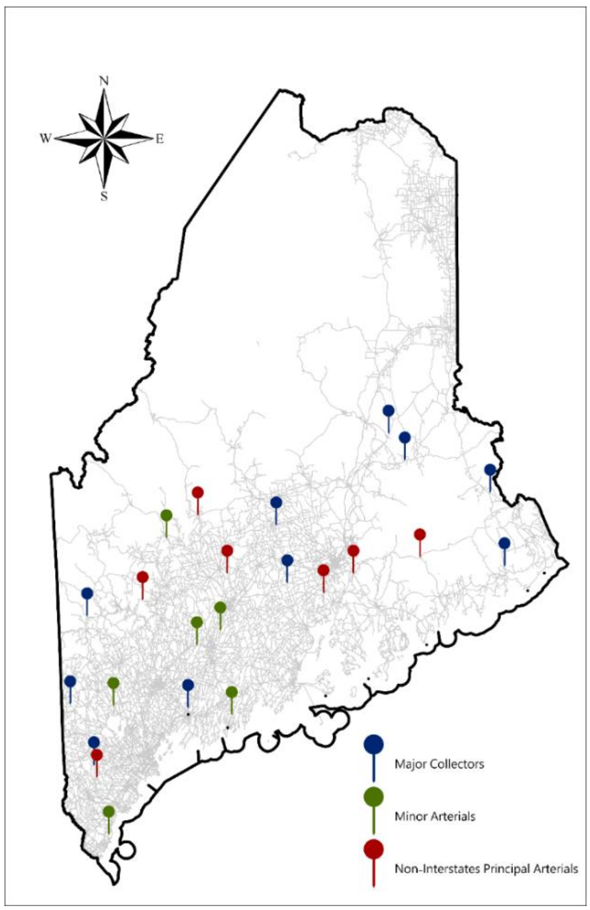


Figure 1: Locations of Count Stations in Maine.

[3] This chapter is reprinted in part from Shahlaee, A., Shirazi, M., Marshall, E., & Ivan, J. N. (2022). Modeling the impact of the COVID-19 pandemic on speeding at rural roadway facilities in Maine using short-term speed and traffic count data. Accident Analysis & Prevention, 177, 106828. This paper is available at the following DOI link: https://doi.org/10.1016/j.aap.2022.106828

Loop detectors at each station collect data in both directions of the roadway. Therefore, each station provides two distinctive sets of traffic count and speed information. Data collected at these stations during the first 28 days of February, April, and May of 2019, 2020, and 2021 were respectively used to represent the duration before the pandemic (or stay-at-home order, to be exact), the stay-at-home order duration, and one year after the order introduction. The 5-minute data collection interval allows short variations of volume and speed to be accounted for analysis. Speed limit information, necessary for determining the amount of speeding, was collected from Main DOT's Public Map Viewer[4] and Google Maps. With this data, the number of the vehicles driving 10, 15, 20 and 25 mph above the speed limit, in each 5-min time interval was found.

A uniform dataset was created with speeding, traffic count, and speed limit information, as well as variables that reflect time of the day (i.e., off peak, morning peak hour, evening peak hour), time of the week (i.e., weekend, and not-weekend) and month of the year (i.e., February, April, May), along with two dummy variables. One dummy variable was set equal to one in April and May 2020 to denote the stay-at-home order, and the other set to one during these times in 2021 to distinguish after the order. Table 2 shows the description of the variables used in this study. The impact of the speed limit variable was modeled as a dummy variable, with the speed limit of 45 mph or less as the reference variable. The time of the day, time of the week, and month of the year variables were also considered as dummies. The off-peak period, weekdays (Monday through Friday), and the month of February were used as reference variables.

Table 2: Data Description.

Variables		Variable Definition
Traffic Count	**Ln (Traffic Count)**	The natural log of 5-min traffic count
Time of day	**Off Peak (=0)**	Data collected during Off Peak (10am-3pm and 7pm to 6am)
	Morning Peak Period	Data collected during Morning Peak Hour (6am-10am)
	Evening Peak Period	Data collected during Evening Peak Hour (3pm-7pm)
Time of Week	**Not Weekend (=0)**	Data collected in weekdays (Monday to Friday)
	Weekend	Data collected in weekends
Month	**February (=0)**	Data collected in February (February 2019, 2020, and 2021)
	April	Data collected in April (April 2019, 2020, and 2021)
	May	Data collected in May (May 2019, 2020, and 2021)
Stay-at-Home Order	**Before Order (=0)**	February, April and May of 2019 and February 2020
	During Order	April and May of 2020 (when stay at home was in place)
	Post Order	February, April and May of 2021
Speed Limit	**≤ 45 mph (=0)**	Speed limit less than or equal to 45 mph
	= 50 mph	Speed limit equals to 50 mph
	= 55 mph	Speed limit equals to 55 mph

After a careful review of the data, we removed data records with interrupted flows, such as those affected by construction zones. Table 3 shows the summary statistics of the 5-minute aggregated traffic count data. As expected, minor and principal arterials carry more traffic compared to major collectors. In addition, the traffic counts are greater during the morning and evening peak periods compared to the off-peak period. The reduction in traffic is also apparent during the COVID-19 stay-at-home order duration (e.g., April and May 2020) for all three facility

[4] https://www.maine.gov/mdot/mapviewer/

types at all times. For example, the maximum 5-min traffic count on minor arterials reduced from 115 to 59 vehicles in April 2020 compared to the same month in 2019.

Table 3: Summary Statistics of the five-minute aggregated traffic count data.

Time Period			Major Collectors				Minor Arterials				Principal Arterials*			
			Mean	S.D.	Min	Max	Mean	S.D..	Min	Max	Mean	S.D.	Min	Max
Morning Peak Period (6 a.m. 10 a.m.)	Feb	2019	5.8	5.7	1	59	14.1	12.3	1	113	12.3	10.4	1	71
		2020	5.8	5.8	1	59	14.3	12.3	1	113	12.4	10.5	1	73
		2021	5.6	5.5	1	52	12.9	10.4	1	84	11.4	9.8	1	72
	April	2019	6.1	6.0	1	53	15.6	13.3	1	115	13.3	11.1	1	73
		2020	4.4	3.9	1	31	9.6	7.6	1	59	8.6	6.9	1	47
		2021	6.1	5.8	1	55	15.0	11.5	1	90	12.9	11.1	1	83
	May	2019	6.6	6.3	1	49	17.5	14.3	1	118	14.7	12.4	1	77
		2020	5.2	4.7	1	37	12.5	9.8	1	70	10.6	8.6	1	53
		2021	6.7	6.2	1	56	17.0	12.7	1	85	14.4	12.3	1	87
Evening Peak Period (3 p.m. 7 p.m.)	Feb	2019	7.3	6.9	1	54	17.8	13.8	1	104	15.8	13.3	1	90
		2020	7.3	7.0	1	49	17.9	13.6	1	102	16.0	13.5	1	88
		2021	6.9	6.6	1	45	16.5	12.6	1	92	14.4	12.4	1	96
	April	2019	7.7	7.3	1	53	20.0	15.0	1	106	16.8	13.8	1	84
		2020	5.6	5.3	1	43	12.5	9.8	1	76	11.0	9.4	1	62
		2021	7.8	7.1	1	54	20.1	14.4	1	94	16.6	14.0	1	75
	May	2019	8.4	7.5	1	52	22.7	16.3	1	107	18.9	15.7	1	88
		2020	7.2	6.4	1	46	17.5	12.8	1	97	14.9	12.2	1	69
		2021	8.5	7.3	1	48	23.1	16.1	1	101	18.8	15.7	1	93
Off peak	Feb	2019	4.4	4.5	1	39	9.1	10.0	1	82	8.2	9.2	1	80
		2020	4.5	4.7	1	65	9.2	10.3	1	80	8.3	9.4	1	83
		2021	4.5	4.7	1	46	9.2	10.4	1	68	8.1	9.5	1	86
	April	2019	4.6	4.7	1	46	10.3	11.3	1	77	8.8	9.8	1	66
		2020	4.1	4.1	1	36	7.6	8.2	1	63	6.6	7.5	1	57
		2021	5.0	5.2	1	48	11.0	12.3	1	82	9.0	10.5	1	81
	May	2019	5.1	5.2	1	72	11.8	13.1	1	86	9.9	11.3	1	84
		2020	4.9	5.0	1	39	10.0	11.1	1	78	8.4	9.7	1	64
		2021	5.3	5.4	1	72	12.5	14.1	1	84	10.0	11.8	1	87

*Non-Interstates Principal Arterials.

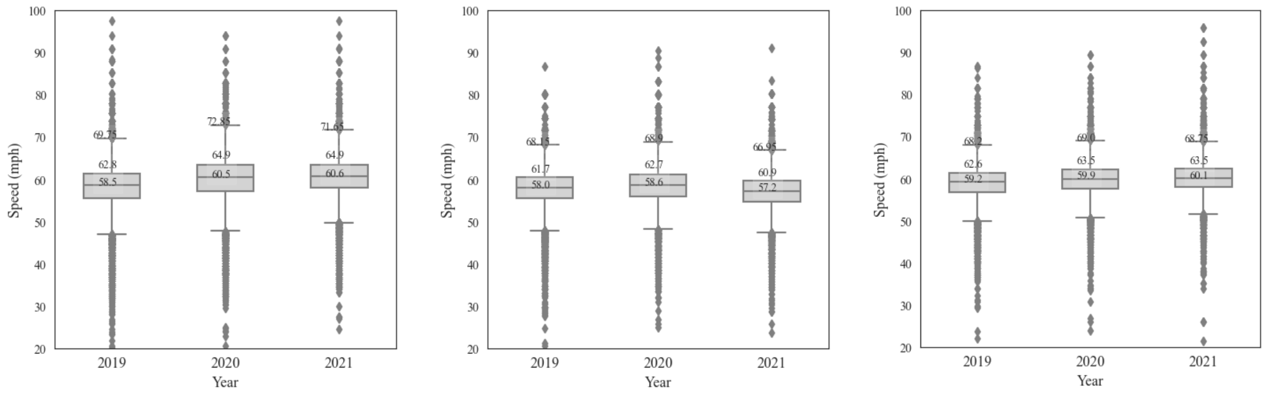
Table 4 shows the distribution of speed at locations with a speed limit of 55 mph on major collectors, minor collectors, and principal arterials. As is evident from this table, the percentage of vehicles driving at higher speeds increased significantly in 2020 and 2021 compared to 2019. For example, the percentage of vehicles driving 5 mph above the speed limit at a location on a major collector roadway increased from 41.17%, to 59.72% during the morning peak period and from 45.02% to 55.21% during evening peak period in April 2020 compared to April 2019. In April 2021, one year after the comprehensive stay-at-home order, the percentage of vehicles driving at 5 mph above speed limit remains at a significantly higher percentage of 58.98% and 57.56% at this location during morning and evening peak periods respectively.

Table 4: Distribution of Speed in 2019, 2020, and 2021 at locations with speed limit of 55 mph

Facility	Time Period			Speed			
				>50mph	>60mph	>70mph	>80mph
Major Collectors (Speed Limit = 55 mph)	**Morning Peak Period (6 a.m. 10 a.m.)**	**April**	**2019**	90.06%	41.17%	2.24%	0.30%
			2020	94.07%	59.72%	5.79%	0.50%
			2021	94.79%	58.98%	5.53%	0.60%
		May	**2019**	93.17%	46.02%	2.97%	0.37%
			2020	93.01%	57.77%	5.43%	0.74%
			2021	95.39%	60.09%	5.11%	0.59%
	Evening Peak Period (3 p.m. 7 p.m.)	**April**	**2019**	91.07%	45.02%	2.57%	0.28%
			2020	90.70%	55.21%	5.11%	0.51%
			2021	92.90%	57.56%	5.00%	0.49%
		May	**2019**	91.58%	46.80%	2.90%	0.39%
			2020	91.23%	58.23%	5.58%	0.66%
			2021	93.20%	59.36%	5.01%	0.61%
	Off peak	**April**	**2019**	87.73%	38.33%	2.42%	0.32%
			2020	90.56%	54.26%	5.38%	0.73%
			2021	91.53%	53.35%	4.61%	0.55%
		May	**2019**	89.49%	42.26%	2.98%	0.43%
			2020	89.96%	52.59%	4.66%	0.60%
			2021	92.50%	54.07%	4.51%	0.52%
Minor Arterials (Speed Limit = 55 mph)	**Morning Peak Period (6 a.m. 10 a.m.)**	**April**	**2019**	89.04%	36.72%	2.48%	0.07%
			2020	92.16%	42.42%	3.97%	0.20%
			2021	93.19%	33.86%	2.00%	0.15%
		May	**2019**	94.18%	40.77%	2.70%	0.17%
			2020	94.04%	43.10%	4.15%	0.29%
			2021	92.83%	33.24%	2.14%	0.25%
	Evening Peak Period (3 p.m. 7 p.m.)	**April**	**2019**	91.10%	39.15%	2.05%	0.06%
			2020	90.62%	38.41%	3.03%	0.17%
			2021	92.93%	38.89%	2.09%	0.25%
		May	**2019**	91.82%	38.15%	1.69%	0.05%
			2020	92.92%	41.35%	3.06%	0.17%
			2021	91.45%	32.90%	1.47%	0.23%
	Off peak	**April**	**2019**	88.59%	33.84%	1.86%	0.08%
			2020	88.70%	34.43%	2.89%	0.15%
			2021	89.42%	31.20%	2.06%	0.17%
		May	**2019**	88.91%	32.29%	1.71%	0.06%
			2020	90.96%	35.89%	2.84%	0.17%
			2021	88.70%	27.47%	1.52%	0.13%
Principal Arterial* (Speed Limit = 55 mph)	**Morning Peak Period (6 a.m. 10 a.m.)**	**April**	**2019**	96.33%	39.21%	2.84%	0.25%
			2020	97.87%	45.82%	3.59%	0.29%
			2021	97.17%	46.07%	4.79%	0.53%
		May	**2019**	96.21%	38.47%	3.06%	0.31%
			2020	97.67%	44.86%	4.30%	0.33%
			2021	97.17%	45.01%	4.83%	0.43%
	Evening Peak Period (3 p.m. 7 p.m.)	**April**	**2019**	96.37%	43.28%	4.02%	0.22%
			2020	96.00%	48.92%	6.24%	0.90%
			2021	98.65%	50.05%	5.77%	0.68%
		May	**2019**	97.05%	41.01%	3.07%	0.23%
			2020	97.84%	47.94%	6.24%	0.60%
			2021	98.42%	51.72%	6.13%	0.64%
	Off peak	**April**	**2019**	94.79%	36.71%	2.60%	0.22%
			2020	96.42%	40.61%	3.48%	0.36%
			2021	96.51%	42.58%	4.29%	0.42%
		May	**2019**	95.73%	34.93%	2.74%	0.29%
			2020	96.32%	40.31%	4.13%	0.42%
			2021	96.62%	40.66%	4.24%	0.49%

*Non-Interstates Principal arterials.

Figure 2 shows the distribution of speed at the three locations documented in Table 4, considering data collected in April and May of 2019, 2020, and 2021. As is evident from this figure, driving at higher speeds had increased significantly in 2020. Although the speed seems to return to the normal condition on the minor arterial location, the figure further illustrates that speed remains high in 2021 for the major collector and none-interstate principal arterial locations.



(a) (b) (c)

Figure 2: Distribution of Speed at (a) Major Collectors, (b) Minor Arterials, and (c) Non-Interstates Principal Arterials

3.2 Methodology

Let us consider the number of cars passing each count station in a short duration of time (here 5 minutes). During each period, n cars pass the station; y out of n cars speed by more than a certain amount (e.g., 10, 15, 20, and 25 mph) with probability of p and $(n-y)$ cars do not speed with probability of $(1-p)$. This would result in a binomial model with odds of $p/(1-p)$. A generalized linear mixed effect Binomial regression model with a logit link function was used to model the odds of speeding for vehicles that drive 10, 15, 20, and 25 mph above speed limit. The random effect term (ε_k) was used to account for the unobserved location heterogeneity at each k-th station. The Binomial probability distribution function is defined as (Hilbe, 2014):

$$p(y_{ik}|p_{ik}, n_{ik}) = \binom{n_{ik}}{y_{ik}} p^{y_{ik}}(1-p_{ik})^{n_{ik}-y_{ik}} \tag{1}$$

where, n_{ik} is the traffic count at the i-th 5-min interval and k-th station, and y_{ik} is the number of vehicles driving at certain number of miles per hour (i.e., 10, 15, 20, and 25 mph) above the speed limit at the same i-th interval and k-th station. A logit function was used to link the speeding percentage (p_{ik}) to the variables described in Table 2. Equation (2) shows the link function.

$$\mathrm{Ln}\left(\frac{p_{ik}}{1-p_{ik}}\right) = \beta_0 + \alpha\,\mathrm{Ln}(V_{ik}) + \sum_{j=1}^{m} \beta_j X_{j,ik} + \gamma_0 I_{d,ik} + \delta_0 I_{p,ik} + \varepsilon_k \tag{2}$$

where,

β_0: Common intercept.

α: Coefficient on the natural log of traffic count.

β_j: Coefficient on the j-th control variable.

γ_0: Coefficient on the Dummy representing stay-at-home order.

δ_0: Coefficient on the Dummy representing after-stay-at home order.

$Ln(V_{ik})$: Natural log of 5-min traffic count at location k for i-th observation.
$X_{j,ik}$: The value of the j-th control variable at location k for i-th observation.
$I_{d,ik}$: Stay-at-home indicator (equal to one if the i-th observation at the k-th station occurred during the stay-at-home order.)
$I_{p,ik}$: Post stay-at-home indicator (equal to one if the i-th observation at the k-th station occurred after the stay-at-home order.)
ε_k: Error term (random effect) at the k-th station.
m: The number of variables in the model.

Specifically, the model included 5-min traffic count (V), a dummy accounting for observations during the stay-at-home order (γ_0), and a dummy accounting for observations after stay-at-home order (δ_0) and a set of variables denoting time-of-day (off-pick, morning peak period, and evening peak period), time of the week (weekend and not weekend), month of the year (February, April, and May), and speed limit as control variables. The model was implemented using the "glmer" package (version 1.1-27.1) (Lee and Grimm, 2018) in R statistical software. Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC) and log-likelihood test statistics were used to evaluate the fit of the models.

3.3. Modeling Results

The mixed effect Binomial model described in Section 4 was used to model odds of speeding for three rural facility types in Maine. Tables 5-7 show the modeling results for major collectors, minor arterials and principal arterials (non-Interstates), respectively. For each facility type, four speeding models were developed to estimate the number of vehicles that drive 10, 15, 20, and 25 mph above the speed limit. The corresponding odds ratios were also calculated and are shown in the tables. For each dataset, the Variance Inflation Factors (VIF) were estimated to test the existence of multicollinearity; the VIF metric was between 1 and 2; hence, no multicollinearity exists among the variables. The final models include variables that are significant at 95% confidence interval.

3.3.1. Major Collectors

Table 5 shows the modeling results for the major collectors. As expected, the traffic count and speeding exhibit a negative association; as the number of vehicles increases, the odds of speeding decreases. Intuitively, it is expected to see fewer vehicles speed by more than 25 mph than 20 mph than 15 mph than 10 mph as the number of vehicles increases, which was well reflected in the modeling results. The odds of speeding by more than 10 mph or 15 mph above the speed limit decreases by about 4% as the natural log of traffic count increases by one unit. The increase in traffic count also has a significant impact on the number of vehicles that are driving 20 and 25 mph above the speed limit. As the natural log of traffic count increases by one unit, the odds of speeding by more than 20 and 25 mph decreases by 38% and 39% respectively.

Time of the day (off peak vs. morning peak period vs. evening peak period), day of the week (weekends vs. weekdays), and different months (e.g., February vs. April vs. May) can significantly influence speeding behavior. The modeling results show that the odds of speeding by more than 10, 20, 20, and 25 mph increases by around 8-10% during the weekends compared to weekdays. Speeding is also more common during the peak periods, especially morning peak periods, presumably because drivers are often in hurry during these times. This hypothesis is well reflected in modeling results. As shown in Table 5, the odds of speeding by more than 10, 15, and 20 mph increases by 20%, 25%, and 16% respectively during the morning peak period, and by

13%, 11%, and 4% during the evening peak periods. The impact of morning and evening peak periods on speeding over 25 mph was insignificant; presumably, this observation is due to higher traffic volume during peak periods that limits the possibility of extreme speeding. It is also worth pointing out that in Maine, the month of February often sees significant snowfall and adverse weather conditions, resulting in reduced speeds. The snowfall and adverse weather conditions are significantly less prevalent in the months of April and May. As shown in Table 5, the odds of speeding 10, 15, 20, and 25 mph above the limit increases by 32%, 31%, 45%, and 59% respectively in April compared to February and by 31%, 29%, 47%, and 68% in May compared to February.

Table 5: Modeling Results for Rural Major Collectors.

Variables	+10 mph Speeding		+15 mph Speeding		+20 mph Speeding		+25 mph Speeding	
	Mean (S.E.)[1]	**Odds Ratio**	**Mean (S.E.)**	**Odds Ratio**	**Mean (S.E.)**	**Odds Ratio**	**Mean (S.E.)**	**Odds Ratio**
Intercept	-1.565 (0.120)		-2.851 (0.122)		-4.122 (0.155)		-5.955 (0.172)	
Ln (Traffic Count)	-0.047 (0.002)	0.954	-0.041 (0.003)	0.960	-0.479 (0.007)	0.619	-0.502 (0.014)	0.606
Weekend	0.074 (0.003)	1.077	0.092 (0.004)	1.096	0.076 (0.011)	1.079	0.081 (0.022)	1.084
Morning Peak Period	0.1834 (0.003)	1.201	0.224 (0.005)	1.251	0.149 (0.012)	1.161	-[2]	-
Evening Peak Period	0.125 (0.003)	1.133	0.103 (0.005)	1.109	0.0414 (0.012)	1.042	-[2]	-
April	0.283 (0.003)	1.327	0.270 (0.005)	1.311	0.375 (0.014)	1.454	0.465 (0.028)	1.591
May	0.276 (0.003)	1.317	0.252 (0.005)	1.286	0.3869 (0.014)	1.472	0.520 (0.028)	1.682
Stay-at-Home (γ_0)	0.237 (0.003)	1.267	0.295 (0.006)	1.343	0.432 (0.014)	1.540	0.509 (0.027)	1.664
Post Stay-at-Home (δ_0)	0.193 (0.003)	1.212	0.237 (0.005)	1.267	0.357 (0.012)	1.429	0.458 (0.023)	1.581
Speed Limit =50 mph	-1.478 (0.249)	0.228	-1.555 (0.235)	0.211	-0.993 (0.214)	0.371	-0.547 (0.283)	0.579
Speed Limit =55 mph	-0.757 (0.133)	0.469	-1.270 (0.174)	0.281	-1.272 (0.268)	0.280	-[2]	-
AIC	2057063		1063567		326235.3		115692.2	
BIC	2057206		1063709		326377.5		115798.9	
Log-Likelihood	-1028520		-531771		-163106		-57837.1	

[1]Values written in parenthesis are standard errors.
[2] Insignificant variables at 95% confidence level.

Most importantly, both dummy variables, which represent the periods during and after the stay-at-home order, are significant with a positive value. This shows that it is not just the reduction in traffic volume that resulted in increased speed during or after the order, but other variables played a role as well. In particular, the odds of speeding by more than 10, 15, 20, and 25 mph increased by 27%, 34%, 54%, and 66% respectively during the order. This observation could be due to reduced traffic enforcement during this time in Maine. Even one year later, the odds of speeding by more than 10, 15, 20, and 25 mph are still 21%, 27%,43% and 58% higher than before the order during the same months. Although these odds are slightly less than during the stay-at-home order (possibly due to resumed enforcement), the results show that drivers have become used to speeding on major collectors during the COVID-19 pandemic.

3.3.2. Minor Arterials

Table 6 shows the modeling results for rural minor arterials. Again, the number of vehicles significantly influences the odds of speeding. Particularly, as the natural log of the traffic count increases by 1 unit, the odds of speeding by more than 10, 15, 20, and 25 mph decreases by 23%, 38%, 57%, and 59% respectively. The reduction in traffic count has a greater impact on minor arterials compared to major collectors. Since minor arterials are designed to carry more traffic, a reduction in traffic gives drivers more opportunities to speed. Like the modeling results for the major collectors, speeding increases during the weekend, morning, and evening peak periods. In particular, the odds of speeding by more than 10, 15, 20, and 25 mph increases by 20%, 15%, 21%, and 24% during the weekends compared to weekdays. When compared to off peak, the odds of speeding by more than 10, 15, and 20 mph increases by 41%, 43%, and 14% respectively during morning peak periods and by 25%, 30%, and 11% respectively during evening peak periods. periods, especially during the morning peak periods, as drivers could be in hurry during these times. As with major collectors, the peak period variable is insignificant for the 25 mph and above model, possibly due to the increased volume reducing opportunities for speeding.

Table 6: Modeling Results for Rural Minor Arterials.

Variables	**+10 mph Speeding**		**+15 mph Speeding**		**+20 mph Speeding**		**+25 mph Speeding**	
	Mean (S.E.)[1]	**Odds Ratio**	**Mean (S.E.)**	**Odds Ratio**	**Mean (S.E.)**	**Odds Ratio**	**Mean (S.E.)**	**Odds Ratio**
Intercept	-2.494 (0.076)		-3.443 (0.147)		-4.704 (0.294)		-6.697 (0.238)	
Ln (Traffic Count)	-0.262 (0.003)	0.769	-0.478 (0.005)	0.620	-0.850 (0.012)	0.427	-0.892 (0.018)	0.410
Weekend	0.184 (0.004)	1.203	0.140 (0.009)	1.150	0.189 (0.023)	1.209	0.217 (0.039)	1.242
Morning Peak Period	0.3421 (0.004)	1.408	0.357 (0.010)	1.429	0.131 (0.028)	1.140	-[2]	-
Evening Peak Period	0.224 (0.004)	1.251	0.264 (0.010)	1.302	0.103 (0.029)	1.109	-[2]	-
April	0.318 (0.005)	1.375	0.433 (0.011)	1.542	0.454 (0.031)	1.574	0.467 (0.052)	1.596
May	0.208 (0.005)	1.231	0.336 (0.011)	1.400	0.434 (0.031)	1.544	0.477 (0.052)	1.611
Stay-at-Home (γ_0)	0.288 (0.004)	1.333	0.274 (0.011)	1.316	0.396 (0.029)	1.487	0.401 (0.049)	1.493
Post Stay-at-Home (δ_0)	-[2]	-	-0.031 (0.010)	0.970	0.084 (0.026)	1.087	0.200 (0.044)	1.222
Speed Limit = 50 mph	-1.373 (0.127)	0.253	-1.675 (0.225)	0.187	-1.077 (0.437)	0.341	-0.687 (0.289)	0.503
Speed Limit = 55 mph	-[2]	-	-1.075 (0.193)	0.341	-0.844 (0.313)	0.430	0.790 (0.279)	2.204
AIC	1232140		389742.8		90946.89		37894.68	
BIC	1232255		389880.9		91084.96		38009.74	
Log-likelihood	-616060		-194859		-45461.4		-18937.3	

[1]Values written in parenthesis are standard errors.
[2] Insignificant variables at 95% confidence level.

The two dummy variables, one signifying times during the stay-at-home order and the other the times after the order, both denote positive coefficients. The first of these two is significantly large, showing that speeds on minor arterials were significantly affected during the stay-at-home order. As shown in Table 6, the odds of speeding by more than 10, 15, 20, and 25 mph increased by 33%, 31%, 49%, and 49% respectively during the order. This observation is likely due to reduced enforcement during this period. In April and May of 2021, speeding by more than 10, and 15 mph seems to return to pre-stay-at-home conditions, but aggressive driving (i.e., speeding by more than 20, and 25 mph) still happens at higher odds. That said, it happens with significantly less frequency than when observed during the order. In particular, the odds of speeding by more than 20 and 25 mph on minor arterials were still 9% and 22% higher than before, even after one year since the order was issued. As noted previously, it is expected to observe a higher number of speeding cases during peak Additionally, the modeling results show that a greater number of vehicles speed during the month of April and May compared to February, due to improved weather conditions.

3.3.3. Principal Arterials

Table 7 shows the modeling results for stations located at rural principal arterial (non-Interstates) facilities. As the natural log of traffic count decreases by one unit, the odds of speeding by more than 10, 15, 20, and 25 mph decreases by 12%, 23%, 35%, and 50%. Similar trends are also observed regarding the time of the week (i.e., weekends), time of the day (i.e., morning, and evening peak periods), and months of the year (i.e., April and May) as the other two facilities. specifically, the odds of speeding by more than 10, 15, 20, and 25 mph increases by 25%, 30%, 34%, and 33% during the weekends compared to weekdays. When compared to off peak, the odds of speeding by more than 10, 15, 20, and 25 mph increases by 11%, 13%, 18% and 17% respectively during morning peak periods and by 11%, 11%, 9% and 9% respectively during evening peak periods. Higher odds of speeding in April and May compared to February is also evident from the results, due to improved weather conditions.

Most importantly, the modeling results show increased odds of speeding during the stay-at-home order. Compared to before, the odds of speeding by more than 10, 15, 20, and 25 mph increased by 39%, 51%, 65%, and 82% respectively. For non-interstates principal arterials, the modeling results show that speeding behavior continues to happen, though to a lesser degree, even one year after the comprehensive order. In particular, the odds of speeding by more than 10, 15, 20, and 25 mph are still 7%, 17%, 25%, and 36% higher than before pandemic.

As a closing note to this section, it is worth pointing out that the modeling results show decreased odds of speeding at higher speed limits (i.e., 50 or 55 mph). The speed limit variable was used as a control variable in the models, but these results are also expected as people intuitively are more inclined to speed on roads with lower speed limits as shown in previous studies (Afghari et al., 2018).

Table 7: Modeling Results for Rural Principal Arterials (Non-Interstates).

Variables	+10 mph Speeding		+15 mph Speeding		+20 mph Speeding		+25 mph Speeding	
	Mean (S.E.)[1]	Odds Ratio	Mean (S.E.)	Odds Ratio	Mean (S.E.)	Odds Ratio	Mean (S.E.)	Odds Ratio
Intercept	-0.751 (0.122)		-2.097 (0.120)		-3.324 (0.159)		-4.387 (0.214)	
Ln (Traffic Count)	-0.130 (0.001)	0.879	-0.260 (0.002)	0.771	-0.426 (0.003)	0.653	-0.687 (0.007)	0.503
Weekend	0.219 (0.002)	1.245	0.260 (0.003)	1.297	0.296 (0.005)	1.344	0.287 (0.012)	1.332
Morning Peak Period	0.105 (0.002)	1.111	0.124 (0.003)	1.132	0.168 (0.006)	1.183	0.162 (0.014)	1.175
Evening Peak Period	0.099 (0.002)	1.105	0.101 (0.003)	1.106	0.081 (0.006)	1.085	0.081 (0.014)	1.085
April	0.194 (0.002)	1.214	0.213 (0.003)	1.237	0.155 (0.007)	1.168	0.151 (0.015)	1.163
May	0.154 (0.002)	1.167	0.168 (0.003)	1.183	0.082 (0.007)	1.086	0.117 (0.015)	1.124
Stay-at-Home (γ_0)	0.326 (0.003)	1.385	0.415 (0.004)	1.514	0.503 (0.007)	1.653	0.600 (0.015)	1.823
Post Stay-at-Home (δ_0)	0.067 (0.002)	1.072	0.161 (0.003)	1.174	0.224 (0.006)	1.251	0.311 (0.013)	1.364
Speed Limit =50 mph	-2.171 (0.100)	0.114	-1.970 (0.196)	0.140	-2.753 (0.459)	0.064	-3.379 (0.350)	0.034
Speed Limit =55 mph	-0.962 (0.258)	0.382	-1.648 (0.513)	0.193	-1.727 (0.392)	0.178	-1.061 (0.361)	0.346
AIC	2658315		1452673		614862.6		227586.7	
BIC	2658455		1452813		615002.5		227726.6	
Log-likelihood	-1329145		-726325		-307419		-113781	

[1]Values written in parenthesis are standard errors.
[2] Insignificant variables at 95% confidence level.

3.4. Summary and Conclusions

The rate of fatal and severe crashes in Maine has increased during the COVID-19 pandemic. During the comprehensive stay-at-home order implemented in Maine, the traffic volume decreased drastically. Drivers responded to this change by increasing their speed. A Binomial mixed effect model was used to model the 5-minute data collected at count stations to understand the impact of the pandemic on speeding on rural facilities. The results show that the odds of speeding by more than 10, 15, 20, and 25 mph on rural major collectors increased by 27%, 34%, 54%, and 66% respectively in April and May of 2020 in comparison to these same months in 2019. Similarly, the odds of speeding by more than 10, 15, 20, and 25 mph increased by 33%, 32%, 49%, and 49% on minor arterials and by 39%, 51%, 65%, 82% on principal arterials during the same duration compared to before. The results also show that the odds of speeding by more than 10, 15, 20, and 25 mph in April and May of 2021 (one year after the stay-at-home order) was still 21%, 27%, 43%, and 58% higher on rural major collectors than the same period before pandemic. The odds of speeding by more than 10, 15, 20, and 25 mph in April and May of 2021on principal arterials is also 7%, 17%, 25%, and 36% higher than the same period in 2019. These results show that many drivers have become accustomed to speeding.

Chapter 4: Speeding on Urban Limited Access Roads

This chapter[5] explores the change in odds of speeding on urban limited access highways (Interstates and freeways) during and after stay-at-home orders imposed in Maine (ME) and Connecticut (CT). The information about speeding and traffic density was derived from probe data provided by StreetLight Insight®. We then used a mixed effect binomial model to establish a link between the odds of speeding and contributing factors denoting the traffic density, roadway geometric characteristics, speed limit, time-related factors, two dummy variables signifying the duration of the stay-at-home order and one year since lifting the order, and several interaction variables. The section contributes to the current literature from multiple perspectives. First, we demonstrate the application of probe data (using hourly traffic volume and speed data from StreetLight Insight®) to analyze the odds of speeding. To the best of our knowledge, limited research, if any, has been devoted to model odds of speeding using hourly probe data. Second, unlike previous studies, we study speeding for the entire network divided into homogenous segments, instead of fixed locations or a specific arterial, taking advantage of the availability of network-level probe data. Third, using data from homogenous segments, we can include different roadway characteristics in the model allowing to measure the effect of variables such as presence of the curve and shoulder width on odds of speeding. Fourth, we establish a link between traffic density or level of service and speeding. To our knowledge, there is also limited research on this topic due to inherent difficulties in estimating the density. However, using the hourly probe data, we can obtain detailed density information, and establish a link between level of service and speeding. Fifth, and most importantly, we investigate how the odds of speeding changed during the stay-at-home order and one year since the onset of the pandemic on urban limited access highways in Maine and Connecticut, especially in morning and evening peak hours. Finally, we explore if there are any differences in odds of speeding between Maine and Connecticut.

4.1. Data Description

This study uses probe data collected from the StreetLight Insight® platform to link speeding with traffic density and several other factors to investigate the impact of the stay-at-home order on speeding on urban limited access highways in two New England states, Maine and Connecticut. To compute the traffic density, the limited access roads were divided into segments with homogenous characteristics (i.e., lane width, shoulder width, speed limit, and number of lanes). Then, the traffic volume and speed data were collected in one-hour aggregated intervals from StreetLight Insight® on roadway segments with speed limits of 50 mph or above for the months of April and May of 2019, 2020, and 2021 using geographic information system (GIS) maps generated for this study. StreetLight uses LBS data collected from cellphones and combines points where devices periodically register their locations (also known as "pings") with common device IDs into trips. These trips show the routes individuals take and their speeds over the route. The platform then uses a Machine Learning algorithm fed with values from permanent count stations to estimate the volume of trips and their speeds to better reflect real values (Streetlight, 2021, 2022). The output data is the volume (q) (vehicle/hour) of vehicles traveling in each hour on each segment, space mean speed (v) (mph), and the distribution of speed on that segment in 1-mph bins.

[5] This chapter is reprinted in part from Marshall, E., Shirazi, M., Shahlaee, A., & Ivan, J. N. (2023). Leveraging probe data to model speeding on urban limited access highway segments: Examining the impact of operational performance, roadway characteristics, and COVID-19 pandemic. Accident Analysis & Prevention, 187, 107038. This paper is available at the following DOI link: https://doi.org/10.1016/j.aap.2023.107038

Using the distribution of the speed, and speed limit information, the percentage of vehicles that drive a certain amount (i.e., 10, 15, and 20 mph) above the speed limit were calculated. To increase the accuracy of the volume and average speed calculation, we removed data points with fewer than 10 vehicle observations. Table 8 shows, on average, the percentage of drivers that speed by more than 10, 15, and 20 mph, during different phases of the pandemic in Maine and Connecticut on roadway segments with the same speed limit. At almost every speed limit, in both states, the percentage of vehicles that speed increased during the stay-at-home orders compared to pre-pandemic. In 2021, a year after the stay-at-home orders, while speeding decreased in some instances compared to the duration of the stay-at-home order, most of the times, it remained higher than the pre-pandemic level.

Table 8: Percentage of speeding on Urban Limited Access Highways in Maine and Connecticut.

State[1]	Speed Limit (mph)	Year[2]	Off Peak			Morning Peak (6-10am)			Evening Peak (3-7pm)		
			10+ mph Speeding	15+ mph Speeding	20+ mph Speeding	10+ mph Speeding	15+ mph Speeding	20+ mph Speeding	10+ mph Speeding	15+ mph Speeding	20+ mph Speeding
ME	**50**	2019	28.0%	12.0%	4.7%	29.3%	13.0%	5.0%	26.9%	11.3%	4.4%
		2020	25.9%	12.8%	5.7%	29.3%	15.5%	7.1%	29.2%	14.7%	6.5%
		2021	34.6%	13.7%	4.3%	40.0%	17.8%	5.9%	37.1%	15.4%	4.9%
	55	2019	30.2%	13.5%	4.4%	31.0%	13.4%	4.3%	32.2%	14.9%	4.9%
		2020	33.7%	16.7%	6.8%	35.4%	17.5%	7.2%	40.2%	21.2%	9.1%
		2021	40.3%	19.4%	6.9%	43.7%	21.8%	7.6%	45.0%	23.2%	8.7%
	60	2019	11.9%	4.4%	1.7%	14.8%	5.6%	2.0%	13.9%	5.0%	1.8%
		2020	13.4%	5.6%	2.5%	16.3%	7.2%	3.2%	16.1%	6.9%	3.1%
		2021	14.0%	4.5%	1.2%	17.7%	6.0%	1.6%	16.1%	5.2%	1.4%
	65	2019	22.2%	7.2%	2.0%	23.2%	7.6%	2.1%	24.9%	8.1%	2.2%
		2020	22.1%	8.6%	3.2%	23.8%	9.6%	3.7%	27.4%	11.2%	3.9%
		2021	25.3%	8.5%	1.9%	26.5%	9.0%	2.0%	29.2%	10.3%	2.3%
	70	2019	8.3%	2.3%	0.7%	9.6%	2.6%	0.8%	8.9%	2.4%	0.7%
		2020	9.2%	3.5%	1.3%	11.9%	4.7%	1.9%	10.8%	3.9%	1.5%
		2021	10.6%	2.8%	0.6%	11.4%	2.9%	0.6%	11.7%	3.0%	0.6%
CT	**50**	2019	48.9%	30.2%	15.3%	52.4%	34.2%	18.2%	49.1%	31.0%	15.8%
		2020	54.7%	35.9%	20.0%	59.4%	40.8%	23.8%	59.3%	40.4%	23.2%
		2021	54.2%	33.7%	17.2%	58.6%	38.4%	20.5%	55.1%	35.3%	18.3%
	55	2019	40.9%	21.6%	9.0%	44.9%	25.9%	11.3%	40.2%	21.8%	9.0%
		2020	47.5%	28.4%	13.9%	51.2%	32.4%	16.8%	51.4%	32.3%	16.2%
		2021	45.0%	24.6%	10.2%	49.5%	29.3%	12.9%	44.8%	25.1%	10.5%
	65	2019	17.3%	5.9%	1.9%	19.4%	6.6%	2.0%	17.3%	5.7%	1.8%
		2020	22.5%	9.5%	3.8%	25.3%	11.1%	4.4%	26.3%	11.4%	4.5%
		2021	22.7%	7.9%	2.1%	26.5%	9.5%	2.4%	24.3%	8.5%	2.2%

[1]Speeding percentage calculated by taking a weighted average of speeding percentage on roadway segments with the same speed limit in each state.
[2] 2019 denotes April and May of 2019 (Pre-Pandemic); 2020 denotes April and May of 2020 (Stay-at-Home Order), and 2021 denotes April and May of 2021 (one year after the order).

Next, the traffic density (K) (vehicle/mile/lane) was calculated using the flow, density, and speed relationship as follows (where n is the number of lanes):

$$K = \frac{q}{n \times v} \tag{1}$$

Table 9 shows the summary statistics of the traffic volume by lane (vehicle/hour/lane), average speed (mph), and traffic density (vehicle/mile/lane) during different times of the day (i.e., morning peak hour from 6 am to 10 am, evening peak hour from 3 pm to 7 pm, and off peak) and different years (or pandemic phases) in Maine and Connecticut. We removed data records with traffic density of 45 vehicles/mile/lane or above, since this range of density corresponds to forcedflow conditions under which speeding is very difficult to occur. As shown in Table 9, the reduction in traffic volume and density and the increase in average speed in April and May of 2020 is evident in most cases, especially during the morning and evening peak hours.

Table 9: Summary Statistics of Traffic Volume, Average Speed and Traffic Density.

State	Speed Limit (mph)	Year[1]	Off Peak[2]			Morning Peak (6am-10am)[2]			Evening Peak (3pm-7pm)[2]		
			Volume Mean (S.D.)	Speed Mean (S.D.)	Density Mean (S.D.)	Volume Mean (S.D.)	Speed Mean (S.D.)	Density Mean (S.D.)	Volume Mean (S.D.)	Speed Mean (S.D.)	Density Mean (S.D.)
ME	50	2019	1658 (867.9)	51.37 (4.104)	14.21 (7.83)	1790 (899)	52.63 (4.696)	15.29 (8.59)	2486 (861.6)	51.11 (4.474)	21.58 (8.671)
		2020	1195 (467.5)	50.73 (7.328)	10.61 (5.173)	1153 (416)	51.93 (7.27)	10.03 (4.578)	1312 (498.5)	51.58 (7.623)	11.49 (5.531)
		2021	1732 (906.5)	55.02 (4.09)	13.91 (7.773)	1417 (551.5)	56.31 (4.303)	11.21 (5.02)	2272 (809.5)	55.53 (3.912)	18.15 (7.5)
	55	2019	1355 (751.3)	58.16 (5.592)	10.25 (5.828)	1374 (740.4)	59.28 (5.031)	10.61 (6.792)	2172 (844)	58.68 (6.022)	16.51 (7.126)
		2020	1007 (436.2)	59.69 (5.489)	7.544 (3.478)	947.2 (382.4)	60.2 (4.923)	7.253 (3.416)	1237 (529.2)	60.85 (5.654)	9.037 (4.13)
		2021	1393 (770.8)	62.01 (4.921)	9.907 (5.585)	1141 (482.8)	63.03 (4.37)	8.198 (4.023)	2000 (736.1)	62.83 (4.95)	14.12 (5.68)
	60	2019	1031 (484.1)	54.84 (6.583)	8.875 (4.512)	985.1 (440.5)	55.9 (6.722)	8.317 (3.981)	1369 (566.8)	55.81 (6.526)	11.61 (5.255)
		2020	894.7 (362.4)	56.39 (5.699)	7.427 (3.264)	732.1 (249.4)	57.61 (6.045)	5.959 (2.219)	1009 (389.3)	57.25 (5.762)	8.264 (3.485)
		2021	1061 (532.9)	58.16 (5.679)	8.561 (4.538)	897 (357.1)	59.45 (6.13)	7.087 (3.079)	1361 (538.2)	58.9 (5.701)	10.86 (4.618)
	65	2019	1141 (629.3)	66.22 (5.903)	7.986 (4.082)	1138 (555.7)	66.74 (6.192)	8.137 (4.342)	1499 (685.8)	66.99 (6.036)	10.54 (4.611)
		2020	838.2 (365.1)	66.01 (6.365)	5.933 (2.538)	822.2 (328)	66.45 (6.305)	5.833 (2.504)	930.6 (405.3)	67.01 (6.443)	6.54 (2.82)
		2021	1140 (682.5)	67.96 (5.524)	7.817 (4.404)	993.7 (463.5)	68.59 (5.259)	6.822 (3.151)	1402 (680.2)	68.92 (5.431)	9.579 (4.35)
	70	2019	955.4 (362.6)	65.8 (6.005)	7.299 (2.783)	915 (316.2)	66.28 (6.206)	6.968 (2.552)	1160 (387.8)	66.54 (6.161)	8.828 (3.217)
		2020	745.3 (248.9)	66.02 (6.017)	5.71 (2.039)	678.1 (209.5)	66.31 (6.481)	5.178 (1.744)	805.7 (269.4)	66.94 (5.879)	6.104 (2.255)
		2021	958.3 (411.2)	67.83 (5.543)	7.096 (3.063)	840.9 (324.6)	68.63 (5.598)	6.178 (2.488)	1149 (374.8)	68.91 (5.236)	8.431 (2.972)
CT	50	2019	2705 (1513)	59.08 (5.955)	17.23 (9.757)	3219 (1447)	60.13 (6.673)	20.65 (10.03)	4214 (1378)	57.75 (7.579)	27.4 (9.098)
		2020	2042 (1100)	61.3 (5.504)	12.69 (7.453)	2191 (979.6)	63.12 (5.18)	13.24 (6.459)	2782 (1237)	62.73 (4.743)	16.93 (8.188)
		2021	2684 (1497)	60.75 (5.638)	16.61 (9.419)	2859 (1276)	62.32 (5.287)	17.58 (8.541)	4045 (1411)	59.95 (7.141)	25.51 (9.131)
	55	2019	2873 (1720)	62.02 (5.456)	18.45 (10.91)	3577 (1626)	62.36 (6.87)	23.48 (10.7)	4442 (1367)	60.49 (7.09)	29.64 (9.192)
		2020	2290 (1389)	63.92 (5.114)	13.99 (8.274)	2564 (1383)	65.4 (4.674)	15.41 (7.414)	3235 (1530)	64.84 (4.833)	20 (9.013)
		2021	2905 (1765)	63.42 (5.351)	18.18 (10.8)	3335 (1552)	63.91 (6.561)	21.21 (9.738)	4295 (1517)	61.9 (7.379)	28.29 (9.739)
	65	2019	2308 (1322)	66.37 (4.439)	13.93 (8.197)	2680 (1282)	66.86 (5.246)	16.34 (8.162)	3686 (1435)	65.82 (5.364)	22.41 (8.671)
		2020	1751 (853.2)	67.81 (4.224)	10.44 (5.747)	1761 (732.1)	68.73 (3.879)	10.33 (4.496)	2195 (977.8)	68.81 (4.025)	13.03 (6.37)
		2021	2347 (1345)	68.19 (4.261)	13.81 (8.132)	2301 (1027)	69.35 (3.769)	13.5 (6.442)	3445 (1375)	68.44 (4.447)	20.31 (8.451)

[1]The average and standard deviation of traffic volume (vehicle/hour/lane), average speed (mph), and density (vehicle/mile/lane) were calculated using data from roadway segments with the same speed limit.

[2] 2019 denotes April and May of 2019 (Pre-Pandemic); 2020 denotes April and May of 2020 (Stay-at-Home Order), and 2021 denotes April and May of 2021 (one year after the order).

We divided the traffic density observations into five groups considering a dummy variable to denote each group. The density range of $0 < K \leq 11$ vehicles/mile/lane denotes LOS of A, $11 < K \leq 18$ vehicles/mile/lane denotes LOS of B, $18 < K \leq 26$ vehicles/mile/lane denotes LOS of C, $26 < K \leq 35$ vehicles/mile/lane denotes LOS of D, and $35 < K \leq 45$ vehicles/mile/lane denotes LOS of E. The LOS of E was considered as the base (or reference) group in the analysis. To create uniform data for modeling, the density data were combined with roadway geometric characteristics, speed limit, time-dependent variables, and two variables denoting the COVID-19 phases, one signifying the duration of the stay-at-home order and the other one year since the onset of the pandemic. We also considered a dummy variable denoting the state (i.e., Maine or Connecticut). Table 10 shows the definition of the variables used in this study.

Table 10: Data Description.

Variables	Classes	Definition
Traffic Density	LOS A ($0 < K \leq 11$)	Density of 0 to 11 vehicle/mile/lane denoting LOS of A
	LOS B ($11 < K \leq 18$)	Density of 11 to 18 vehicle/mile/lane denoting LOS of B
	LOS C ($18 < K \leq 26$)	Density of 18 to 26 vehicle/mile/lane denoting LOS of C
	LOS D ($26 < K \leq 35$)	Density of 26 to 35 vehicle/mile/lane denoting LOS of D
	LOS E ($35 < K \leq 45$) (=0)	Density of 35 to 45 vehicle/mile/lane denoting LOS of E
Time of the Week	Weekday (=0)	Weekdays (Monday-Friday)
	Weekend	Weekend (Saturday-Sunday)
Time of the Day	Off Peak (=0)	Off peak hours (10 am-3 pm and 7 pm-6 am)
	Morning Peak Period	Moring Peak hours (6 am-10 am)
	Evening Peak Period	Evening peak hours (3 pm-7 pm)
COVID-19 Phases	Before Stay-at-Home (=0)	Data collected in April and May of 2019
	Stay-at-Home	Data collected in April and May of 2020
	Post Stay-at-Home	Data collected in April and May of 2021
Speed Limit	Speed Limit ≤55 (=0)	Segments with speed limit less than or equal to 55 mph
	Speed Limit = 60 mph	Segment with a speed limit of 60 mph
	Speed Limit = 65 mph	Segment with a speed limit of 65 mph
	Speed Limit = 70 mph	Segment with a speed limit of 70 mph
Presence of Curve	No Curve (=0)	No curve (straight alignment)
	Curve Presence	Presence of horizontal curve
Shoulder Width	Wide Shoulder (=0)	Shoulder wider ≥ 6 feet
	Narrow Shoulder	Shoulder wider < 6 feet
State	Maine	Data collected on limited access roads in Maine
	Connecticut (=0)	Data collected on limited access roads in Connecticut

We considered two time-dependent dummy variables in the models. One variable signifies the time of the day, and it is denoted by "M" if it indicates the morning peak hours and by "E" if it denotes the evening peak hours. The other variable signifies the time of the week, and it is denoted by "W" if it is weekend. The off-peak period and weekdays were considered as the base (or reference) groups in analysis. We also included dummy variables related to several geometric characteristics of the roadway. All roadway segments had standard 12-ft lanes, so the lane width variable was not considered in modeling. The shoulder width however varies across the segments. We considered a dummy variable to account for the effect of shoulder width that is less than 6 ft. This dummy variable was denoted by "SW". We also considered a dummy variable for the presence of a horizontal curve. This dummy variable was denoted by "HC". The speed limit in Maine varies from 50 to 70 mph. we considered a speed limit of 50 or 55 mph as the base (or reference) group, and considered dummy variables signifying speed limits of 60, 65, and 70 mph. In Connecticut, the speed limits of roadway segments are 50, 55, and 65 mph. Again, we considered the speed limits of 50 and 55 mph as the base (or reference) groups and considered a dummy variable signifying the speed limit of 65 mph. Finally, we considered two dummy variables to account for COVID-19 phases, one signifying the duration of the stay-at-home order (April and May 2020) denoted by "ϒ" and the other, one year since the onset of the pandemic (April and May 2021) denoted by "δ" to respectively measure the impact of pandemic during and after the stay-at-home order. These dummy variables are compared with the pre-pandemic duration (April and May 2019).

As a closing note to this section, it is worth pointing out that the stay-at-home period in Maine and Connecticut started in the middle of March 2020, when states issued orders for non-essential workplaces, dining, lodging non-essential retail, and schools to close or work remotely. Furthermore, both states limited maximum gathering sizes. In Maine, these restrictions began to be eased on June 1, 2020. In Connecticut, outdoor dining as well as some non-essential retail and museums were allowed to reopen from May 20, 2020; however, schools and workplaces remained closed and remote during the entire month of May; we considered data from the months of April and May for analysis, where major daily or commuter trips such as those to work and school remained restricted.

4.2. Methodology

We used a mixed effect binomial regression model with a logit link function to correlate the odds of speeding with a set of dummy variables described in Table 8. The mixed effect model was used to account for location heterogeneity and repeated observations for each segment over time. Let us assume q_{is} and $\mathrm{y_{is}}$ respectively denote the traffic volume (vehicle/hr.), and the number of vehicles that speed by more than a certain amount (e.g., 10, 15, or 20 mph) above the speed limit on segment "s" during the i-th one-hour time interval. Likewise, let us assume $\mathrm{P_{is}}$ denotes the probability of speeding on segment "s" during the same i-th time interval. Then, the binomial model can be written as described in Eq. (2):

$$\mathrm{y_{is}} \sim \mathrm{Binomial}(\mathrm{P_{is}}, \mathrm{q_{is}}) \equiv \binom{\mathrm{q_{is}}}{\mathrm{y_{is}}} \mathrm{P_{is}}^{\mathrm{q_{is}}-\mathrm{y_{is}}} (1-\mathrm{P_{is}})^{\mathrm{y_{is}}} \tag{2}$$

A logit link function was used to correlate the odds of speeding $\left(\frac{\mathrm{P_{is}}}{1-\mathrm{P_{is}}}\right)$ with a set of dummy variables as shown in Eq. (3).

$$\begin{aligned} \mathrm{Logit}\,(\mathrm{P_{is}}) &= \mathrm{Ln}\left(\frac{\mathrm{P_{is}}}{1-\mathrm{P_{is}}}\right) \\ &= \pi + \left(\mathrm{K_A} \times \mathrm{I_{A,is}} + \mathrm{K_B} \times \mathrm{I_{B,is}} + \mathrm{K_C} \times \mathrm{I_{C,is}} + \mathrm{K_D} \times \mathrm{I_{D,is}}\right) \\ &+ \left(\mathrm{SL_{60}} \times \mathrm{I_{SL60,s}} + \mathrm{SL_{65}} \times \mathrm{I_{SL65,s}} + \mathrm{SL_{70}} \times \mathrm{I_{SL70,s}} + \mathrm{HC} \times \mathrm{I_{HC,s}} + \mathrm{SW} \times \mathrm{I_{SW,s}}\right) \\ &+ \left(\mathrm{W} \times \mathrm{I_{w,i}} + \mathrm{M} \times \mathrm{I_{M,i}} + \mathrm{E} \times \mathrm{I_{E,i}}\right) + \left(\Upsilon \times \mathrm{I_{\Upsilon,i}} + \delta \times \mathrm{I_{\delta,i}}\right) \\ &+ \left(\mathrm{M\Upsilon} \times \mathrm{I_{M\Upsilon,i}} + \mathrm{E\Upsilon} \times \mathrm{I_{E\Upsilon,i}} + \mathrm{M\delta} \times \mathrm{I_{M\delta,i}} + \mathrm{E\delta} \times \mathrm{I_{E\delta,i}}\right) + \varepsilon_s \end{aligned} \tag{3}$$

Where

π: common intercept (constant)

K_A, K_B, K_C, and K_D: Coefficients on dummy variables denoting LOS of A, B, C, and D, respectively.

$I_{A,is}$, $I_{B,is}$, $I_{C,is}$, and $I_{D,is}$: Dummy variables, respectively, denoting LOS of A, B, C, and D, on segment "s" during the i-th time interval (=1 if LOS is "A", "B", "C", or "D", and =0 otherwise.)

SL_{60}, SL_{65}, and SL_{70}: Coefficients on dummy variables denoting speed limit of 60 mph, 65 mph, and 70 mph, respectively.

$I_{SL60,s}$, $I_{SL65,s}$, and $I_{SL70,s}$: Dummy variables, respectively, denoting speed limit of 60 mph, 65 mph, and 70 mph on segment "s" (=1 if speed limit is 60 mph, 65 mph, or 70 mph, and =0 otherwise.)

HC: Coefficient on dummy variable denoting the presence of the horizontal curve.

$I_{HC,s}$: Dummy variable denoting the presence of the horizontal curve on segment "s" (=1 if present, and = 0 if not present.)

SW: Coefficient on dummy variable denoting a narrow (less than 6ft) shoulder width.

$I_{SW,s}$: Dummy variable denoting a narrow shoulder width for segment "s" (= 1 if shoulder width is less than 6ft, and =0 otherwise.)

W, M , and E: Coefficients on dummy variables denoting the weekend, morning peak hour, and evening peak hour, respectively.

$I_{W,i}$, $I_{M,i}$, and $I_{E,i}$: Dummy variables, respectively, denoting the weekend, morning peak hours, and evening peak hours at the i-th time interval (=1 if weekend, morning, or evening peak, and =0 otherwise.)

ϒ: Coefficient on dummy variable denoting the stay-at-home order.

$I_{ϒ,i}$: Dummy variable denoting the stay-at-home order at the i-th time interval (=1 if stay-at-home order, and =0 otherwise.)

δ: Coefficient on dummy variable denoting the post stay-at-home order.

$I_{\delta,i}$: Dummy variable denoting the post stay-at-home order at the i-th time interval (=1 if post stay-at-home order, and =0 otherwise.)

Mϒ: Coefficient on dummy variable denoting the interaction of the morning peak hours and stay-at-home order.

Eϒ: Coefficient on dummy variable denoting the interaction of the evening peak hours and stay-at-home order.

Mδ: Coefficient on dummy variable denoting the interaction of the morning peak hours and post stay-at-home order.

Eδ: Coefficient on dummy variable denoting the interaction of the evening peak hours and post stay-at-home order.

$I_{Mϒ,i}$: Dummy variable denoting the interaction of the morning peak hours and stay-at-home order at the i-th time (=1 if stay-at-home order and morning peak hours, and =0 otherwise.)

$I_{Eϒ,i}$: Dummy variable denoting the interaction of the evening peak hours and stay-at-home order at the i-th time (=1 if stay at-home-order and evening peak hours, and =0 otherwise.)

$I_{M\delta,i}$: Dummy variable denoting the interaction of the morning peak hours and post stay-at-home order at the i-th time (=1 if post stay-at-home order and morning peak hours, and =0 otherwise.)

$I_{E\delta,i}$: Dummy variable denoting the interaction of the evening peak hours and post stay-at-home order at the i-th time (=1 if post stay at home order and evening peak hours, and =0 otherwise.)

ε_s: The random effect component for segment "s" (normally distributed).

To compare speeding in Maine and Connecticut, we also developed models with combined Maine and Connecticut data, with dummy variables that denote Maine (I_{ME}), interaction of Maine and stay-at-home order ($I_{ME,\Upsilon}$) and interaction of Maine and post stay-at-home order ($I_{ME,\delta}$) variables. Due to differences in speed limit in Connecticut and Maine, we only used a dummy variable that denotes the speed limit of 65 mph and greater (i.e., =1 if speed limit is 65 mph or above, and =0 otherwise). Therefore, the following link function (Eq. 4) was used to model data.

$$\begin{aligned} \text{Logit}\ (P_{is}) &= \text{Ln}\left(\frac{P_{is}}{1-P_{is}}\right) \\ &= \pi + \left(K_A \times I_{A,is} + K_B \times I_{B,is} + K_C \times I_{C,is} + K_D \times I_{D,is}\right) \\ &+ \left(SL_{\geq 65,s} \times I_{SL\geq 65,s} + HC \times I_{Hc,s} + SW \times I_{SW,s}\right) \\ &+ \left(W \times I_{w,i} + M \times I_{M,i} + E \times I_{E,i}\right) + \left(\Upsilon \times I_{\Upsilon,i} + \delta \times I_{\delta,i}\right) \\ &+ \left(M\Upsilon \times I_{M\Upsilon,i} + E\Upsilon \times I_{E\Upsilon,i} + M\delta \times I_{M\delta,i} + E\delta \times I_{E\delta,i}\right) \\ &+ \left(ME \times I_{ME} + ME\Upsilon \times I_{ME,\Upsilon} + ME\delta \times I_{ME,\delta}\right) + \varepsilon_s \end{aligned} \tag{4}$$

4.3. Modeling Results

This section documents the modeling results. First, the data in Maine and Connecticut were used separately to develop models for these states. Then, the data in both states were combined and used in an aggregated model to explore the difference in speeding between Maine and Connecticut. We used log-likelihood, AIC, and BIC metrics to select the final model. We analyzed both correlation and multicollinearity among explanatory variables, and no significant correlation or multicollinearity was observed in data. Variables reported in final models are significant at 95% Confidence Interval.

4.3.1. Maine Models

Table 11 shows the modeling results for urban limited access highways in Maine. The odds of speeding in Maine increased as the LOS of roadways improves. For speeding of 10 mph or more, the odds of speeding increases by 29% for a LOS of D, 60% for a LOS of C, 89% for a LOS of B, and 99% for a LOS of A when compared to a LOS of E. Similarly, for speeding of 15 mph or more, the odds of speeding increases by 26% for a LOS of D, 59% for a LOS of C, 93% for a LOS of B, and 2.09 times for a LOS of A compared to a LOS of E. Lastly, for speeding of 20 mph or more, the model shows that the odds of speeding increases by about 15%, 41%, 71%, and 93% for LOS of D, C, B, and A respectively compared to LOS of E.

In addition to an increase in the odds of speeding for lower traffic densities (better levels of service), the model also shows that the odds of speeding during the morning and evening peak hours are greater than one, even before the pandemic. This indicates that the odds of speeding increases during peak hours compared to off-peak. In particular, before the pandemic, the odds of speeding by more than 10, 15, and 20 mph (controlling for the other factors) increased by 18%, 17%, and 12% respectively during the morning peak hours and by about 19%, 18%, and 14% respectively during the evening peak hours, compared to off peak hours. In addition, the odds of speeding in Maine also increases during the weekend, with the odds of speeding by more than 10, 15, and 20 mph increasing by 43%, 44%, and 40% respectively compared to weekdays.

Table 11: Modeling Results for Urban Limited Access Highways in Maine.

Category	Variables	+10 mph Speeding		+15 mph Speeding		+20 mph Speeding	
		Mean (S.E.)[1]	**Odds Ratio**	**Mean (S.E.)[1]**	**Odds Ratio**	**Mean (S.E.)[1]**	**Odds Ratio**
Intercept	**Constant (π)**	-1.437 (0.03180)	-	-2.619 (0.03460)	-	-3.750 (0.03280)	-
Traffic Density (or LOS)	**LOS A (0 < K ≤ 11) (K_A)**	0.689 (0.00084)	1.99	0.739 (0.00120)	2.09	0.655 (0.00200)	1.93
	LOS B (11 < K ≤ 18) (K_B)	0.6237 (0.00083)	1.89	0.658 (0.00120)	1.93	0.533 (0.00190)	1.71
	LOS C (18 < K ≤ 26) (K_C)	0.472 (0.00083)	1.60	0.466 (0.00120)	1.59	0.345 (0.00190)	1.41
	LOS D (26 < K ≤ 35) (K_D)	0.257 (0.00087)	1.29	0.228 (0.00130)	1.26	0.135 (0.00210)	1.15
Time Variables	**Morning Peak Period (M)**	0.161 (0.00027)	1.18	0.152 (0.00040)	1.17	0.116 (0.00068)	1.12
	Evening Peak Period (E)	0.174 (0.00024)	1.19	0.163 (0.00035)	1.18	0.127 (0.00060)	1.14
	Weekend (W)	0.357 (0.00014)	1.43	0.366 (0.00020)	1.44	0.332 (0.00033)	1.40
Pandemic phases	**Stay-at-Home (ϒ)**	0.032 (0.00027)	1.03	0.182 (0.00038)	1.20	0.373 (0.00060)	1.45
	Post Stay-at-Home (δ)	0.258 (0.00021)	1.29	0.220 (0.00031)	1.25	0.061 (0.00053)	1.06
Pandemic Phases and Time of the day	**Morning Peak × Stay-at-Home (Mγ)**	0.034 (0.00046)	1.04	0.065 (0.00064)	1.07	0.104 (0.00010)	1.11
	Evening Peak × Stay-at-Home (Eγ)	0.110 (0.00040)	1.12	0.123 (0.00056)	1.13	0.129 (0.00088)	1.14
	Morning Peak × Post Stay-at-Home (Mδ)	0.009 (0.00039)	1.01	0.025 (0.00055)	1.03	0.033 (0.00095)	1.03
	Evening Peak × Post Stay-at-Home (Eδ)	0.044 (0.00033)	1.05	0.077 (0.00046)	1.08	0.118 (0.00080)	1.13
Segment Features	**Curve Presence (HC)**	-0.316 (0.00014)	0.73	-.266 (0.0500)	0.77	-0.195 (0.05400)	0.82
	Shoulder Width < 6ft. (SW)	-[2]	-	-[2]	-	-[2]	-
	Speed Limit = 60 (SL_{60})	-1.32 (0.04200)	0.27	-1.33 (0.05800)	0.26	-1.196 (0.06200)	0.30
	Speed Limit = 65 (SL_{65})	-0.65 (0.05300)	0.56	-0.91 (0.03700)	0.40	-1.10 (0.04200)	0.33
	Speed Limit = 70 (SL_{70})	-1.84 (0.06100)	0.16	-2.07 (0.23100)	0.13	-2.21 (0.08700)	0.11
Goodness-of-Fit Metrics	**AIC**	63579918		89288802		111434338	
	BIC	63580147		89289030		111434566	
	log-Likelihood	-31789940		-44644382		-55717150	

[1]Standard errors
[2] Insignificant at 95% Confidence Interval.

Most importantly, the modeling results show an increase in the odds of speeding during and after the COVID-19 stay-at-home order implementation. During the COVID-19 restriction, at the off-peak hours, the odds of speeding increased by 3% for speeding of at least 10 mph, 20% for speeding of at least 15 mph and 45% for speeding of at least 20 mph. Furthermore, the odds ratio of speeding increases by an additional factor (in addition to the increase during the off-peak hours) of 1.04, 1.07, and 1.11 times during the morning, and 1.12, 1.13-, and 1.14- times during evening peak hours for speeding by more than 10, 15 and 20 mph. This will result in increased odds of 7%, 28% and 61% during the morning peak hours, and 15%, 36% and 65% during the evening peak hours for speeding by more than 10, 15 and 20 mph respectively, compared to pre pandemic.

Likewise, even after almost one year since the time that the stay-at-home order was lifted, during the off-peak hours, the odds of speeding continued to be above pre-pandemic levels by 29% for speeding of at least 10 mph, 25% for speeding of at least 15 mph, and 6% for speeding of at least 20 mph. In addition, the odds ratio of speeding increased by additional factor (in addition to observed increase during off-peak hours) of 1.01, 1.03, and 1.03 times during the morning and 1.05, 1.08 and 1.13 times during the evening peak hours. This results in an increased odds of 31%, 29%, and 9% during the morning and 35%, 35% and 20% during the evening for speeding greater than 10, 15, and 20 mph respectively compared to before pandemic. The results show that although the odds of speeding by more than 20 mph reduced compared to during the stay-at-home order, the odds of speeding by more than 10 mph increased in the state after stay-at-home order, presumably due to increased perceived risk by drives after the order.

Examining geometric characteristics, the model shows that the impact of a narrower shoulder width (less than 6 ft.) on the odds of speeding by more than 10, 15 and 20 mph is insignificant. Furthermore, the results show 27% reduction in odds for speeding of more than 10 mph, 23% for speeding of more than 15 mph, and 18% for speeding of more than 20 mph on curves compared to tangents. The modeling results also showed decreased odds of speeding when speed limit is greater than 60 mph (i.e., it is 60, 65, or 70 mph) compared to smaller speed limits of 50 and 55 mph.

4.3.2. Connecticut Models

Table 12 shows the modeling results for urban limited access highways in Connecticut. As Shown in Table 12 the odds of speeding increases as traffic density decreases (or as the level of service improves). In particular, the odds of speeding by more than 10 mph increases by 23% at LOS of D, by 48% at LOS of C, by 72% at LOS of B and 76% at LOS of A compared to a LOS of E. Likewise, the odds of speeding by more than 15 mph increases by 23% at LOS of D, by 48% at LOS of C, by 75% at LOS of B and by 88% at LOS of A compared to LOS of E. Finally, the odds of speeding by more than 20 mph increases by 27% at LOS of D, 56% at LOS of C, 91% at LOS of B and 2.18 times at LOS of A.

Table 12: Modeling Results for Urban Limited Access Highways in Connecticut.

Category	Variables	+10 mph Speeding		+15 mph Speeding		+20 mph Speeding	
		Mean (S.E.)[1]	Odds Ratio	Mean (S.E.)[1]	Odds Ratio	Mean (S.E.)[1]	Odds Ratio
Intercept	Constant (π)	-0.745 (0.005000)	-	-1.73 (0.016000)	-	-2.88 (0.005300)	-
Traffic Density (or LOS)	LOS A ($0 < K \leq 11$) (K_A)	0.565 (0.000051)	1.76	0.631 (0.000061)	1.88	0.778 (0.000085)	2.18
	LOS B ($11 < K \leq 18$) (K_B)	0.539 (0.000045)	1.72	0.560 (0.000055)	1.75	0.646 (0.000078)	1.91
	LOS C ($18 < K \leq 26$) (K_C)	0.389 (0.000042)	1.48	0.392 (0.000051)	1.48	0.447 (0.000072)	1.56
	LOS D ($26 < K \leq 35$) (K_D)	0.206 (0.000041)	1.23	0.209 (0.000050)	1.23	0.240 (0.000073)	1.27
Time Variables	Morning Peak Period (M)	0.207 (0.000048)	1.23	0.260 (0.000059)	1.30	0.274 (0.000083)	1.32
	Evening Peak Period (E)	0.052 (0.000050)	1.05	0.072 (0.000064)	1.08	0.096 (0.000091)	1.10
	Weekend (W)	0.385 (0.000026)	1.47	0.346 (0.000030)	1.41	0.307 (0.000042)	1.36
Pandemic phases	Stay-at-Home (Υ)	0.236 (0.000042)	1.27	0.331 (0.000050)	1.39	0.416 (0.000069)	1.52
	Post Stay-at-Home (δ)	0.230 (0.000036)	1.26	0.203 (0.000045)	1.23	0.132 (0.000065)	1.14
Pandemic Phases and Time of the day	Morning Peak × Stay-at-Home ($M\gamma$)	-0.005 (0.000074)	1.00	-0.024 (0.000087)	0.98	-0.013 (0.00012)	0.99
	Evening Peak × Stay-at-Home ($E\gamma$)	0.201 (0.000070)	1.22	0.206 (0.000085)	1.23	0.196 (0.00012)	1.22
	Morning Peak × Post Stay-at-Home ($M\delta$)	0.012 (0.000067)	1.01	-0.00055 (0.000082)	1.00	-0.002 (0.00011)	1.00
	Evening Peak × Post Stay-at-Home ($E\delta$)	0.064 (0.000066)	1.07	0.051 (0.000083)	1.05	0.039 (0.00012)	1.04
Segment Features	Curve Presence (HC)	-0.059 (0.008600)	0.94	-[2]	-	-[2]	-
	Shoulder Width < 6 ft. (SW)	-0.163 (0.014000)	0.85	-0.175 (0.032000)	0.84	-0.188 (0.016000)	0.83
	Speed Limit = 65 (SL_{65})	-1.42 (0.008800)	0.24	-1.75 (0.01800)	0.18	-2.01 (0.007300)	0.13
Goodness-of-Fit Metrics	AIC	2115114525		1658782658		1193904392	
	BIC	2115114786		1658782919		1193904638	
	log-Likelihood	-1057557245		-829391311		-596952179	

[1]Standard errors.
[2]Insignificant at 95% Confidence Interval.

The modeling results show that in Connecticut, even before pandemic, the odds of speeding during the morning and evening peak hours were higher than the off-peak hours. Specifically, speeding by more than 10, 15, and 20 mph respectively increases by 23%, 30% and 32% during the morning and by 5%, 8% and 10% during the evening peak hours compared to off-peak hours. In addition, in Connecticut, the odds of speeding increases during the weekend compared to weekdays. Specifically, speeding by more than 10, 15 and 20 mph increases by 47%, 41% and 36% during the weekends compared to weekdays. The modeling results show a significant increase in odds of speeding in Connecticut during the COVID-19 pandemic. Specifically, the odds of speeding by at least 10 mph increased by 27%, speeding by at least 15 mph by 39%, and speeding by at least 20 mph by 52% during off-peak hours. The model also included variables to determine the increases in odds of speeding during the morning and evening peak hours. The odds of speeding during the morning peak hours increased at almost the same rate as the off-peak hours during the pandemic. During the evening peak hours, however, the odds ratio of speeding by more than 10, 15, and 20 mph increased by an additional factor (in addition to the increase during the off-peak hours) of 1.22, 1.23, and 1.22 during the stay-at-home order, and additional factor of 1.07, 1.05, and 1.04 one year since the stay-at-home order. This will result in increased odds of 55%, 71% and 85% during the stay-at-home order, and 35%, 29%, and 19% one year after lifting the order for speeding greater than 10, 15, 20 mph during the evening peak hours.

The dummy variable denoting the presence of curves was only significant for speeding by more than 10 mph. Specifically, the odds of speeding by 10 mph decreases by about 6% on curves compared to tangents on limited access highways in Connecticut. The shoulder width dummy variable was shown to be significant in Connecticut. The modeling results show that the narrower shoulder (less than 6 ft.) results in decreased odds of speeding. Specifically, the odds of speeding by more than 10, 15 and 20 mph decrease by 15%, 16% and 17% respectively when the shoulder is narrower than 6 ft. As noted earlier, in Connecticut, Most Freeways and Interstates have a Speed limit of 65 mph; there are no segments with a speed limit of 60 mph, or 70 mph or above. Therefore, we only considered a dummy variable for speed limit of 65 mph. Similar to the results in Maine, The odds of speeding decreases at higher speed limits of 65 mph. As shown in Table 12, the odds of speeding by more than 10, 15 and 20 mph are respectively 76%, 82% and 87% lower on segments with speed limits of 65 mph compared to segments with lower speed limits.

4.3.3. Combined Models

A model with combined Maine and Connecticut data was developed to compare the odds of speeding between the two states. The combined model included a dummy variable indicating “Maine”, as well as variables that accounted for the interactions of the “Maine” variable and the variables denoting the pandemic phases (during and one year after the stay-at-home duration). Therefore, the modeling results help show how the odds of speeding were affected in the two states, compared before and after the pandemic. The results of this model are shown in Table 13. The negative sign for the coefficient on the “Maine” dummy variable indicates that the odds of speeding in Maine is lower than Connecticut. In fact, before the pandemic, the odds of speeding by at least 10 mph, 15 mph and 20 mph were respectively 43%, 52% and 58% lower in Maine compared to Connecticut. The modeling results also show that during the stay-at-home order, the odds ratios of speeding by at least 10 mph, 15 mph, and 20 mph increased at a lower rate in Maine compared to Connecticut; specifically, during the stay-at-home order, the odds for speeding greater than 10 mph, 15 mph, and 20 mph were increased respectively at 19%, 14%, and 4% lower rate in Maine compared to Connecticut. Lastly, the modeling results show that one year after the restriction period, the increased odds of speeding in Maine remained about the same as Connecticut, with a slightly increase in odds ratio for speeding greater than 10 mph (2% increase) and 15 mph (4% increase), but smaller odds for speeding of 20 mph or more (3% decrease).

Table 13: Modeling Results for Urban Limited Access Highways in Maine and Connecticut.

Category	Variables	+10 mph Speeding		+15 mph Speeding		+20 mph Speeding	
		Mean (S.E.)[1]	Odds Ratio	Mean (S.E.)[1]	Odds Ratio	Mean (S.E.)[1]	Odds Ratio
Intercept	**Constant (π)**	-0.800 (0.015000)	-	-1.79 (0.003600)	-	-2.93 (.0042)	-
Traffic Density (or LOS)	**LOS A ($0 < K \leq 11$) (K_A)**	0.568 (0.000050)	1.76	0.632 (0.000060)	1.88	0.778 (0.000085)	2.18
	LOS B ($11 < K \leq 18$) (K_B)	0.541 (0.000045)	1.72	0.562 (0.000054)	1.75	0.647 (0.000077)	1.91
	LOS C ($18 < K \leq 26$) (K_C)	0.390 (0.000041)	1.48	0.393 (0.000050)	1.48	0.448 (0.000072)	1.57
	LOS D ($26 < K \leq 35$) (K_D)	0.207 (0.000041)	1.23	0.210 (0.000050)	1.23	0.240 (0.000073)	1.27
Time Variables	**Morning Peak Period (M)**	0.206 (0.000047)	1.23	0.258 (0.00040)	1.29	0.272 (0.000083)	1.31
	Evening Peak Period (E)	0.057 (0.000049)	1.06	0.076 (0.000061)	1.08	0.098 (0.000090)	1.10
	Weekend (W)	0.384 (0.000025)	1.47	0.346 (0.000030)	1.41	0.307 (0.000041)	1.36
Pandemic phases	**Stay-at-Home (Υ)**	0.236 (0.000042)	1.27	0.331 (0.000049)	1.39	0.415 (0.000069)	1.52
	Post Stay-at-Home (δ)	0.230 (0.000036)	1.26	0.207 (0.000038)	1.23	0.131 (0.000065)	1.14
Pandemic Phases and Time of the day	**Morning Peak × Stay-at-Home (Mγ)**	-0.004 (0.000073)	1.00	-0.022 (0.000076)	0.98	-0.012 (0.000120)	0.99
	Evening Peak × Stay-at-Home (Eγ)	0.196 (0.000069)	1.22	0.203 (0.000083)	1.23	0.194 (0.000120)	1.21
	Morning Peak × Post Stay-at-Home (Mδ)	0.012 (0.000066)	1.01	-[2]	-	-0.002 (0.000110)	1.00
	Evening Peak × Post Stay-at-Home (Eδ)	0.063 (0.000065)	1.07	0.052 (0.000078)	1.05	0.040 (0.000120)	1.04
Segment Features	**Curve Presence (HC)**	-0.100 (0.017000)	0.90	-0.074 (0.004200)	0.93	-0.041 (0.006200)	0.96
	Shoulder Width < 6ft. (SW)	-0.073 (0.028000)	0.93	-0.081 (0.008100)	0.92	-0.097 (0.006500)	0.91
	Speed Limit ≥ 65 ($SL_{\geq 65}$)	-1.270 (0.017000)	0.28	-1.60 (0.004900)	0.20	-1.86 (0.005600)	0.16
State	**Maine (ME)**	-0.566 (0.031000)	0.57	-0.733 (0.007700)	0.48	-0.862 (0.004200)	0.42
	Maine×Stay-at-Home (MEΥ)	-0.210 (0.000180)	0.81	-0.146 (0.000250)	0.86	-0.046 (0.000390)	0.96
	Maine×Post-Stay-at-Home (MEδ)	0.023 (0.000150)	1.02	0.039 (0.000210)	1.04	-0.032 (0.000360)	0.97
Goodness-of-Fit Metrics	**AIC**	2227274597		1748556563		1257706411	
	BIC	2227274902		1748556854		1257706717	
	log-Likelihood	-1113637277		-874278261		-628853185	

[1]Standard errors.
[2]Insignificant variable at 95% confidence Interval.

4.4. Summary and Conclusions

As the number of drivers on roadways drastically reduced with the onset of the COVID-19 Pandemic, traffic speeds increased. This study used mixed effect binomial regression models with a logit link function to correlate the odds of speeding with dummy variables indicative of traffic density, highway geometric characteristics, temporal variables such as time of the day and time of the week, phases of the stay-at-home order, and several interaction variables. Using emerging probe datasets, this study was able to provide a unique, network level perspective showing how these dummy variables affected the odds of speeding on limited access highways in Maine and Connecticut. Furthermore, since the data were collected at hourly intervals, the models are based on detailed data, improving their representation of true network conditions.

The modeling results are consistent with the results in the previous chapter. Using data from probes rather than count stations, however, we were able to study speeding patterns across the highway network. In addition, we further explored the change in odds of speeding during peak hours, during the stay-at-home order and one year since that. Particularly, the results showed that during the time when stay-at-home orders were in place, the odds of speeding by more than 10, 15, and 20 mph increased by 55%, 71% and 85% respectively in Connecticut, and by 15%, 36%, and 65% respectively in Maine the during evening peak hours, compared to pre-pandemic levels. Similarly, the study showed that even after one year since the stay-at-home orders were lifted, the odds of drivers speeding remained elevated relative to where they were prior to COVID-19. One year after the lifting of restrictions, the odds of speeding greater than 10, 15, and 20 mph during the evening peak hours were still 35%, 29%, and 19% greater in Connecticut and 35% 35% and 20% greater in Maine than prior to the pandemic.

With the use of hourly probe datasets (i.e., hourly volume and space mean speed), this study was also able to include traffic density in the model, reflected as dummies for different levels of service. The modeling results show how the odds of speeding changes as the compaction of vehicles on a roadway change. It was found that compared to an LOS of E, improved LOSs of D, C, B, and A all have increased odds of speeding, with the greatest increase in odds being for speeding of 20 mph or more, as seen in Tables 11- 13. In each case, as the level of service improves, the odds of speeding increases. This establishes a link between lower traffic densities, or better roadway service, and greater speeding and potentially more severe crashes. Regarding the roadway characteristics, the modeling results show that narrower shoulder width and curve presence leads to lower odds of speeding. In Maine and Connecticut, the odds of speeding reduced for speed limits greater than 60 mph (i.e., it is 60, 65, or 70 mph) compared to smaller speed limits of 50 and 55 mph; these findings are consistent with other studies (Afghari et al., 2018).

Since the probe data used in this study was collected from cellphones, the data covers the entire network across two states. Consequently, the difference in the odds of speeding, and the changes in these odds during and after the COVID-19 stay-at-home orders could be captured in the model on a broader scale. Using a dummy to denote the "state" and modelling the interactions between the state dummy variable and the COVID-19 dummy variables, the model shows that the odds of speeding in Maine were lower pre-pandemic than the odds of speeding in Connecticut, with the odds of speeding in Maine becoming less than those of Connecticut (or, more likely, the odds of speeding in Connecticut becoming even greater) during the stay-at-home orders. Following the lifting of the stay-at-home order, the odds of speeding in Maine have been lower than the odds of speeding in Connecticut by levels about equal to pre-pandemic conditions.

Chapter 5: Crash Models

This chapter contributes to existing literature in three important ways. First, we model the effect of operational speed on crash occurrence after the pandemic closures. Generally, models that relate operating speed to crash occurrence are challenging to estimate and studied less frequently than other models in transportation safety literature. The models estimated in this study will help to identify variables that influence the crash occurrence in new conditions which have emerged since the COVID-19 pandemic closures. Second, we leverage emerging probe data to perform a network level analysis of the crash occurrence. Previous studies mainly relied on speed data collected at permanent count stations or a specific arterial, rather than an entire network. Accessing the hourly probe data along all controlled access highway segments in the study area, all these segments could be incorporated in the model. Lastly, by utilizing data through the end of 2022 in our analysis, we are using data to model very recent conditions. Few if any reviewed papers have published analysis performed using data so recent in their analysis of emerging conditions following the COVID-19. This current study aims to address this gap in research by modeling total and fatal-injury crash occurrence using short duration models.

5.1. Data Description

This study used emerging probe datasets from the StreetLight InSight® platform to collect volume and speed information on limited access highway segments in Maine. Since 2011, StreetLight harnessed hundreds of data sources that contribute to their RouteScience® engine. StreetLight's Metrics are primarily derived from Location Based Services (LBS) and Connected Vehicle Data (CVD), along with GPS data, Commercial truck data for a range of weight classes, thousands of vehicular/bicycle/pedestrian sensors, land use data/parcel data, census characteristics, and more. LBS data are derived from systems on cellphones, collecting points when the phones register their location. Every phone has its own identification code, so the platform uses these IDs and time information to generate "trips" or the pathways that a vehicle has followed. These trips are fed into a Machine Learning algorithm along with permanent count stations data, so the volume and speeds of vehicles obtained match real world conditions. This is then extrapolated to the entire network to estimate the traffic conditions. CVD is based on location "pings" from vehicles with onboard location systems as opposed to cellphones. When the platform is queried for information, relevant trip information is aggregated based on the requested times and provided GIS map, providing volume and speed estimates for each segment (Streetlight, 2021, 2022). The provided estimates are hourly volume (q) (vehicles/hour), average speed (v) (mph), and a distribution of the speeds travelled by the vehicles in percentage form, for every one mile per hour between 50 and 100 mph.

Using geometric characteristics data, roadways were divided into homogenous segments with similar features. For example, if the speed limit, curvature, shoulder width, or lane count changed, a new segment was delineated. These segments were compiled into a Geographic Information System (GIS) map and used with the StreetLight InSight® platform to obtain the hourly volume and speed data. Data were collected for controlled access highways (Interstates and freeways) in Maine, from January to December of 2018 and 2019, representing the pre-pandemic duration, and 2021, and 2022, representing the pandemic effect. Review of the data revealed that the 2018 data were less complete than that of 2019, 2021, and 2022, so it was decided to screen the data to ensure that any average segment-hours were based on at least 10 observations. For each segment, then, the average hourly volume, average hourly speed, and coefficient of variation of hourly speed were calculated for each time of day (e.g., 9-10 am), time of the week (e.g., weekdays) and year (e.g., 2022). Therefore, for each segment, 24 (number of hours in a day) × 2 (weekdays vs. weekends) × 4 (number of years) = 192 records were derived.

Crash data for a given year was merged with the StreetLight data by segment, year, time of the week, and hour of the day. Animal crashes were removed from the dataset because their occurrence is random and depends more on conditions unrelated to the operational performance of the roadway, such as animal habitats and behavior. The crash occurrence was modeled as a binary response variable; if a crash occurred, the response variable is 1.0 and if not, the response variable is 0.0. If multiple crashes occurred on a given segment in the same hour during a year, a new entry of the average traffic conditions of that crash was created. For example, if there were two crashes between 8am-9am on a segment during weekends in 2021, this hour's records would be repeated in two observations, one for each crash as opposed to being a single observation. This was done with the objective of weighing the segment and operational characteristics under which crashes occurred.

The effects of the COVID-19 pandemic on vehicle speeds can be seen below in Tables 14 and 15. Table 14 shows the summary statistics of hourly speed information considering all roadway segments. For this purpose, the average, standard deviation (S.D.) and coefficient-of-variation (CV) of hourly speed were estimated for each segment. Then, the mean and S.D of these estimates were calculated across all segments and reported in Table 14. These statistics show that from before to after the restriction period, the average roadway speeds generally increased. The standard deviations of speed had variable behavior, in some cases decreasing, while in other cases increasing shortly after the restriction period in 2021 but decreasing in 2022 to less than that of 2019. Table 15 shows the Total (KABCO) and Fatal-Injury (KABC) crash counts that were recorded during the different studied time periods on urban and rural roadways of different speed limits.

Table 14: Mean and Standard Deviation[1] of Hourly Speed Information Calculated Across All Segments.

Urban / Rural	Speed Limit	Year	Weekday									Weekend		
			Morning Peak			Evening Peak			Off Peak					
			Avg Hourly Speed	S.D. of Hourly Speed	C.V. of Hourly Speed	Avg. Hourly Speed	S.D. of Hourly Speed	C.V. of Hourly Speed	Avg. Hourly Speed	S.D. Hourly Speed	C.V. Hourly Speed	Avg. Hourly Speed	S.D. of Hourly Speed	C.V. of Hourly Speed
Urban	50	2018	48.3 (3.32)[1]	3.6 (0.485)	0.0752 (0.0126)	46.0 (3.31)	4.32 (0.929)	0.0953 (0.0244)	47.2 (2.97)	3.6 (0.585)	0.0768 (0.015)	49.7 (2.9)	3.51 (0.677)	0.0712 (0.0155)
		2019	50 (3.03)	3.56 (0.581)	0.0712 (0.0112)	47.9 (3.2)	4.00 (1.42)	0.0849 (0.0346)	50.1 (2.66)	3.4 (0.826)	0.0678 (0.0163)	52.3 (2.95)	2.86 (0.704)	0.0549 (0.0144)
		2021	55.1 (2.8)	2.64 (0.345)	0.048 (0.0065)	53.7 (2.52)	3.22 (1.000)	0.0601 (0.0189)	54.1 (2.45)	3.26 (0.942)	0.0604 (0.0181)	55.8 (2.47)	2.91 (0.596)	0.0523 (0.011)
		2022	58.3 (3.22)	2.3 (0.421)	0.0396 (0.007)	56.2 (2.58)	3.05 (1.31)	0.0544 (0.0237)	56.9 (2.89)	3.0 (1.5)	0.0532 (0.028)	58.5 (2.85)	2.37 (0.815)	0.0408 (0.0148)
	55	2018	56 (5.79)	3.62 (0.648)	0.0655 (0.0141)	54.3 (6.86)	4.45 (1.09)	0.0844 (0.0279)	54.8 (6.24)	3.67 (0.867)	0.0684 (0.0199)	57.7 (6.47)	3.62 (0.791)	0.0638 (0.0164)
		2019	54.7 (3.42)	3.87 (0.704)	0.0712 (0.0142)	53.5 (4.67)	4.20 (1.31)	0.0801 (0.0302)	54.9 (4.00)	3.54 (0.732)	0.0649 (0.0146)	57.6 (4.5)	2.87 (0.59)	0.0505 (0.0125)
		2021	61.5 (2.67)	2.87 (0.488)	0.0467 (0.00842)	60.5 (3.66)	3.43 (1.23)	0.0575 (0.023)	60.6 (3.4)	3.25 (1.01)	0.0544 (0.0191)	62.7 (3.56)	3.14 (0.665)	0.0504 (0.0117)
		2022	64.8 (2.55)	2.41 (0.486)	0.0374 (0.00815)	63.5 (3.41)	3.62 (1.88)	0.0581 (0.033)	63.9 (3.15)	3.26 (1.44)	0.0518 (0.0248)	66 (2.85)	2.39 (0.765)	0.0366 (0.0126)
	60	2018	50.7 (4.49)	4.05 (0.466)	0.0805 (0.0123)	50.3 (4.52)	3.98 (0.509)	0.0799 (0.0139)	50.3 (4.66)	4.03 (0.591)	0.0812 (0.0158)	53.1 (4.88)	3.73 (0.622)	0.0713 (0.0159)
		2019	53.3 (4.83)	3.98 (0.483)	0.0753 (0.0115)	53.0 (4.62)	3.75 (0.488)	0.0713 (0.0114)	52.9 (4.63)	3.78 (0.65)	0.0721 (0.0151)	55.1 (4.79)	3.37 (0.717)	0.062 (0.0156)
		2021	58.9 (4.5)	3.18 (0.618)	0.0545 (0.0124)	58.1 (4.42)	3.11 (0.537)	0.054 (0.0115)	57.5 (4.38)	3.44 (0.97)	0.0605 (0.0184)	59 (4.58)	3.19 (0.607)	0.0547 (0.0124)
		2022	63.4 (4.28)	2.74 (0.78)	0.0436 (0.0134)	62.6 (4.14)	2.85 (0.69)	0.046 (0.0125)	62.2 (4.3)	2.78 (0.781)	0.0452 (0.0143)	63 (4.42)	2.89 (0.933)	0.0464 (0.0161)
	65	2018	63.7 (5.16)	3.45 (0.868)	0.055 (0.0159)	63.5 (5.36)	4.05 (1.14)	0.0649 (0.0205)	63.7 (5.46)	3.32 (1.09)	0.0533 (0.0202)	65.5 (4.86)	3.31 (1.12)	0.0515 (0.02)
		2019	62.3 (5.83)	4.08 (0.896)	0.0664 (0.0171)	62.1 (5.91)	4.13 (1.03)	0.0676 (0.0199)	62.7 (5.49)	3.69 (0.909)	0.0595 (0.0165)	65.1 (5.35)	3.11 (0.866)	0.0484 (0.0149)
		2021	67 (4.52)	2.96 (0.669)	0.0446 (0.0122)	66.8 (4.62)	3.23 (0.782)	0.0489 (0.0138)	66.5 (4.56)	3.01 (0.806)	0.0458 (0.0145)	68.1 (4.33)	3.19 (0.826)	0.0473 (0.0142)
		2022	70.5 (4.2)	2.64 (0.862)	0.0378 (0.0135)	69.9 (4.21)	3.04 (0.983)	0.0439 (0.0157)	69.4 (4.38)	2.78 (1.00)	0.0407 (0.0165)	70.8 (4.02)	2.52 (1.00)	0.036 (0.0154)
Rural	65	2018	63.7 (5.16)	3.45 (0.868)	0.055 (0.0159)	63.5 (5.36)	4.05 (1.14)	0.0649 (0.0205)	63.7 (5.46)	3.32 (1.09)	0.0533 (0.0202)	65.5 (4.86)	3.31 (1.12)	0.0515 (0.02)
		2019	62.3 (5.83)	4.08 (0.896)	0.0664 (0.0171)	62.1 (5.91)	4.13 (1.03)	0.0676 (0.0199)	62.7 (5.49)	3.69 (0.909)	0.0595 (0.0165)	65.1 (5.35)	3.11 (0.866)	0.0484 (0.0149)
		2021	67 (4.52)	2.96 (0.669)	0.0446 (0.0122)	66.8 (4.62)	3.23 (0.782)	0.0489 (0.0138)	66.5 (4.56)	3.01 (0.806)	0.0458 (0.0145)	68.1 (4.33)	3.19 (0.826)	0.0473 (0.0142)
		2022	70.5 (4.2)	2.64 (0.862)	0.0378 (0.0135)	69.9 (4.21)	3.04 (0.983)	0.0439 (0.0157)	69.4 (4.38)	2.78 (1.00)	0.0407 (0.0165)	70.8 (4.02)	2.52 (1.00)	0.036 (0.0154)

[1]Numbers in parentheses show the standard deviations.

Table 15: Summary statistics of crashes by roadway type and speed limit.

Urban/Rural	Year	Weekday						Weekend	
		Morning Peak		Evening Peak		Off Peak			
		KABCO	KABC	KABCO	KABC	KABCO	KABC	KABCO	KABC
Urban	2018	69	19	125	21	39	12	37	69
	2019	114	38	184	45	93	20	53	114
	2021	49	7	104	34	96	33	68	49
	2022	79	30	96	23	88	25	73	79
Rural	2018	103	33	122	32	85	20	78	19
	2019	158	39	163	42	186	49	147	29
	2021	87	25	119	28	146	41	191	50
	2022	145	36	159	47	150	47	136	38

Figures 3-8 show the distribution of hourly speed, with Figures 3-5 showing morning, evening, and off-peak speed distributions respectively for urban roadways, and figures 6-8 showing the same respective distributions for rural roadways. These plots show normal distributions drawn from the mean and standard deviation of hourly speed for each study year on a random segment. These figures show that since the COVID-19 pandemic, there was an increase in average speed and a change in the standard deviation of speed. Overall, average speeds increased in 2021-2022 compared to 2018-2019. Standard deviations of speed tended to decrease in 2021-2022 as compared to 2018-2019, however, because of the higher mean speeds, the standard deviations caused the tails of the distribution to extend to higher speed ranges.

Three types of variables were used in the model: (1) geometric characteristics, (2) operational characteristics, (3) dummy variables signifying the years 2021 and 2022. Geometric characteristics were considered as dummy variables. These dummy variables denote segments with curves (curve present =1), narrow shoulder widths (narrower than six feet=1), and number of lanes (more than two lanes =1). Operational characteristics include the log of average hourly volume, average hourly speed, and the CV of hourly speed. All these variables are continuous. Lastly, dummy variables were also included to denote the years of 2021 and 2022 (compared to 2018 and 2019 that represent the pre-pandemic condition). These dummy variables were used to track the effect of the pandemic in 2021 and 2022 separately compared to pre-pandemic years. In other words, these dummies capture the effect, if any, of these post-pandemic years that cannot be accounted for by operational speed variables in the model, as well as identifying if the effect is decaying or transitory. Table 16 shows the variables included in the models.

Table 16: Data Description.

Variable Type	Variable	Definition
Operational Characteristics	Ln (Average Volume)	Natural log of average hourly volume (continuous variable)
	Average Hourly Speed	Average hourly speed (continuous variable)
	CV of Hourly Speed	CV of average hourly speed (continuous variable)
Year	2021	Dummy variable for the year 2021
	2022	Dummy variable for the year 2022
	2018 and 2019 (=0)	Base condition, representing 2018 and 2019 (pre-pandemic)
Roadway Characteristics	Curve	Dummy variable denoting curve presence
	Tangent (=0)	Base condition for curve dummy, denotes straight road
	Narrow shoulder	Dummy variable denoting shoulder width of less than 6 ft.
	Wider shoulder (=0)	Base condition for shoulder width dummy
	More Than Two Lanes	Dummy variable denoting segments with more than two lanes (in one direction)
	Two Lanes (=0)	Base condition, indicates only two lanes in one direction

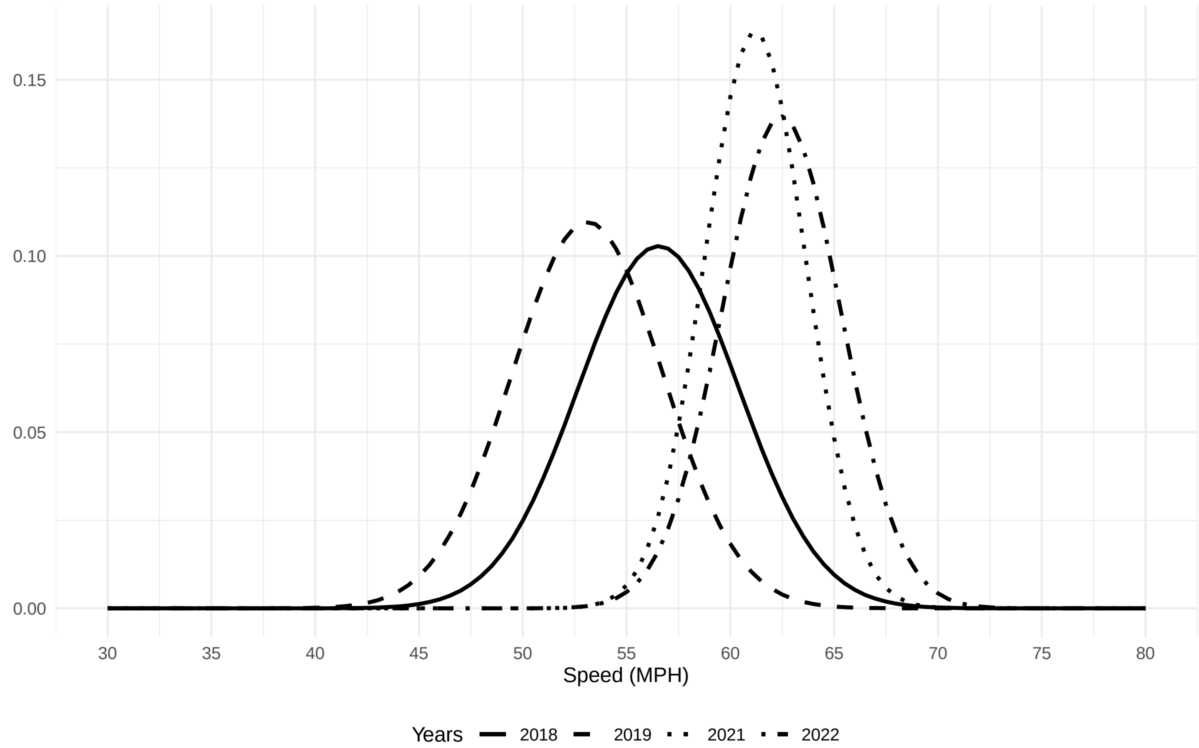


Figure 3. Speed distribution plots for a urban roadway segment, for 9-10am for 2018, 2019, 2021, and 2022.

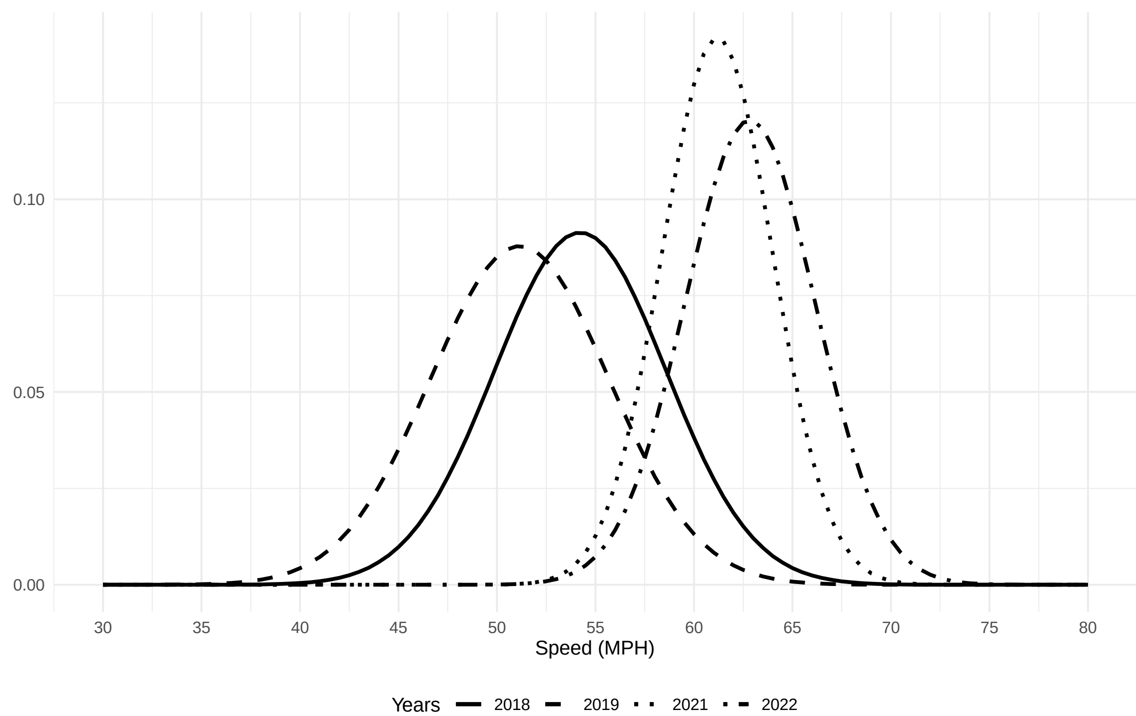


Figure 4: Speed distribution plots for a urban roadway segment, for 5-6pm for 2018, 2019, 2021, and 2022.

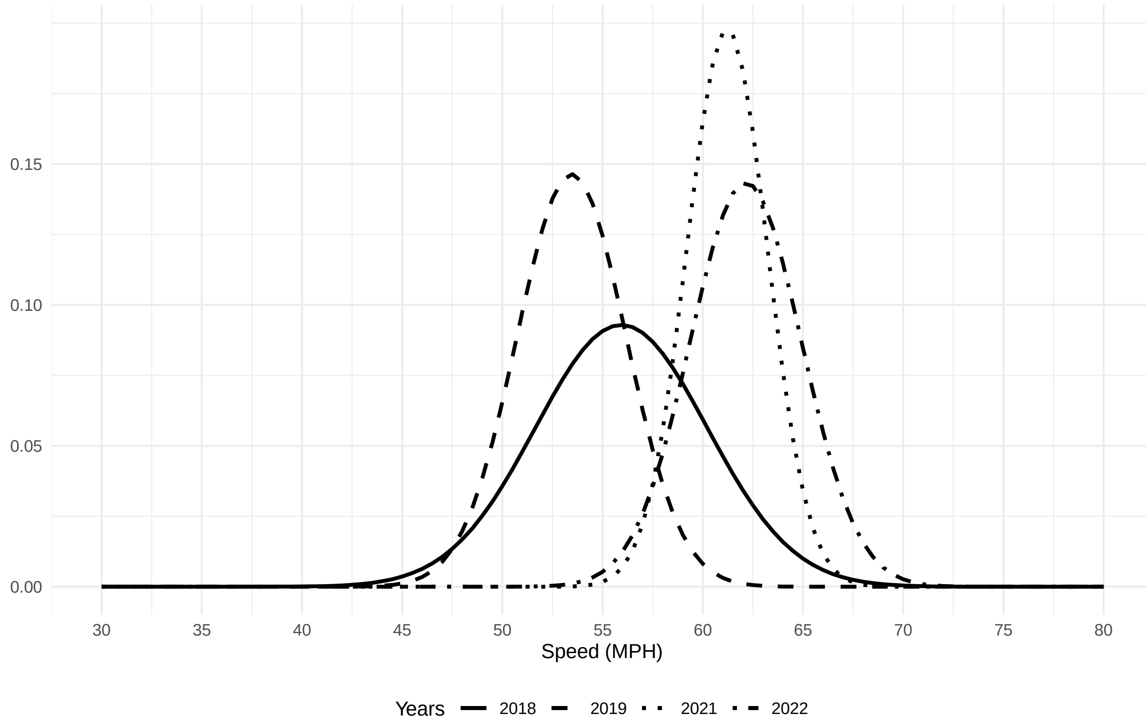


Figure 5: Speed distribution plots for a urban roadway segment, for 11-12am for 2018, 2019, 2021, and 2022.

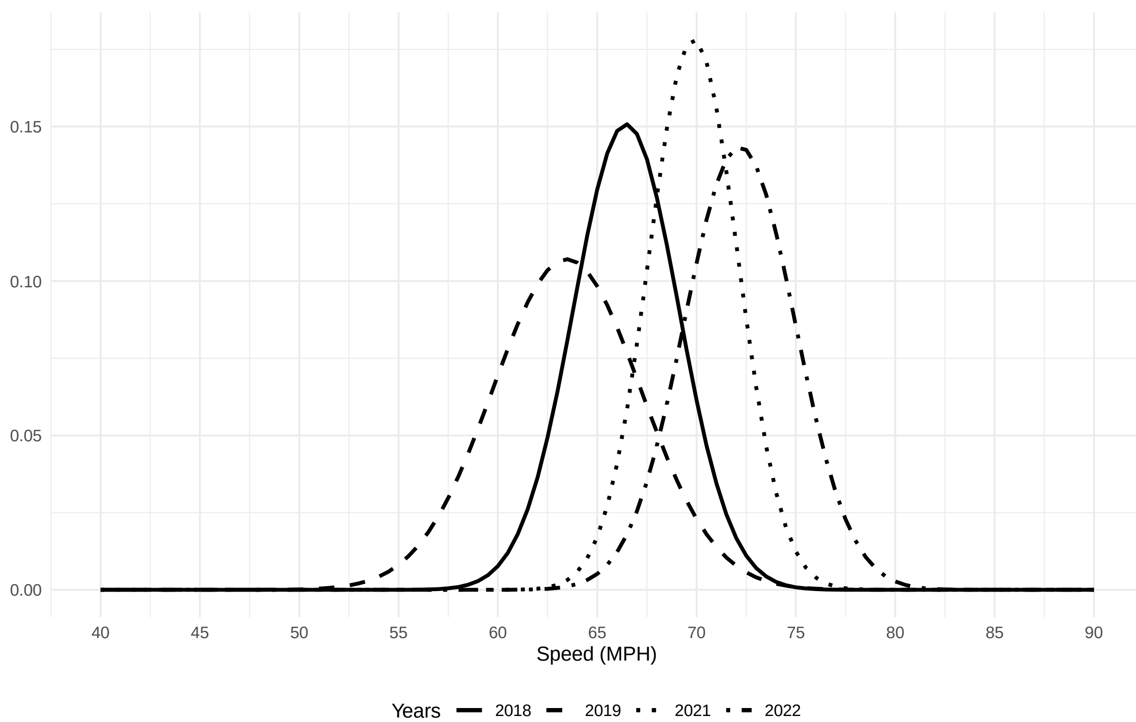


Figure 6: Speed distribution plots for a rural roadway segment, for 9-10am for 2018, 2019, 2021, and 2022.

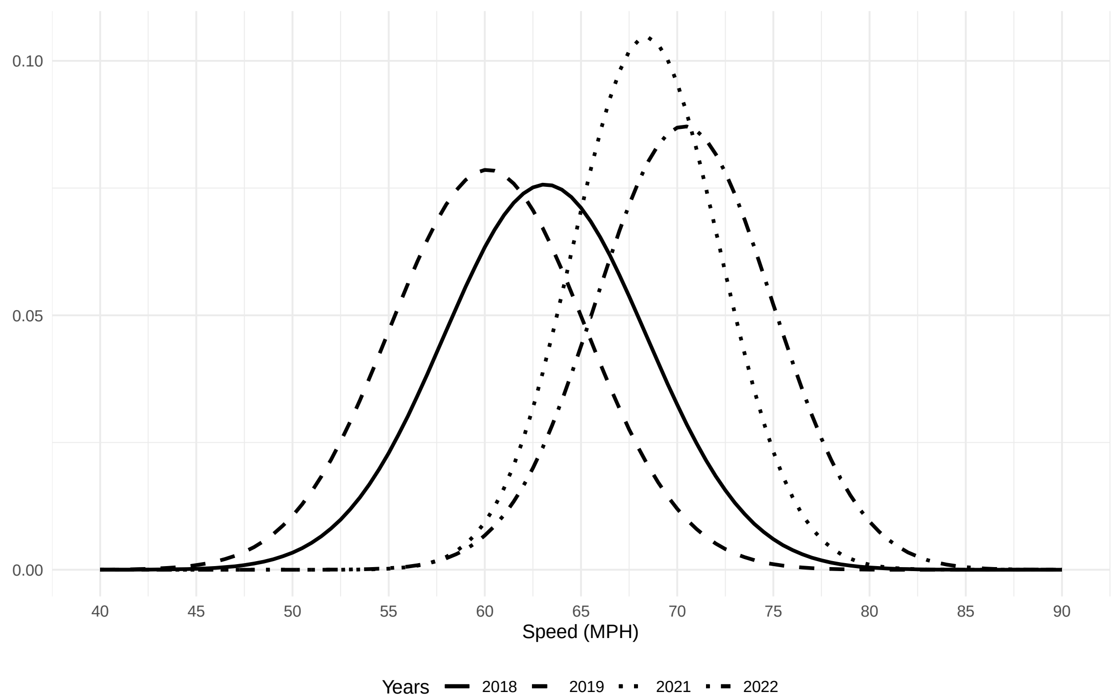


Figure 7: Speed distribution plots for a rural roadway segment, for 5-6pm for 2018, 2019, 2021, and 2022.

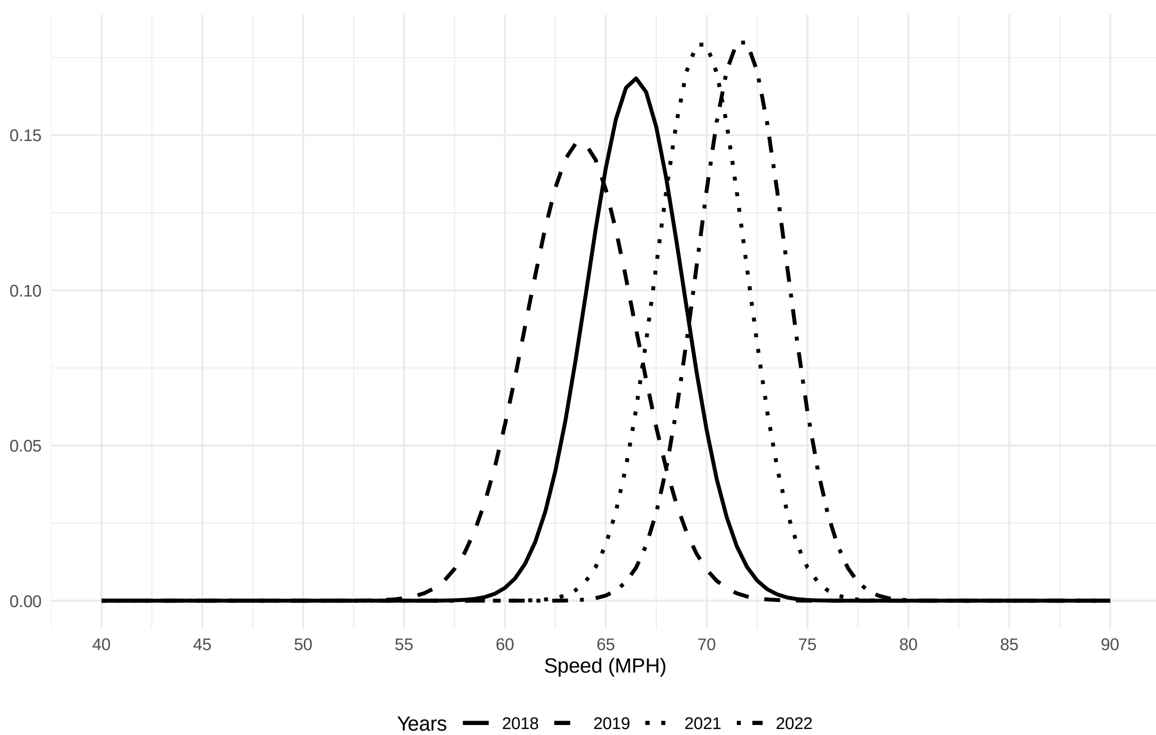


Figure 8: Speed distribution plots for a rural roadway segment, for 11-12am for 2018, 2019, 2021, and 2022.

5.2. Methodology

We estimated a total of 16 separate models, half for urban crashes (four for KABCO and four KABC crashes) and half for rural crashes (four for KABCO and four KABC crashes). Each set of four models consists of one for weekday morning peak hours (6-10am), one for weekday evening peak hours (3-7pm), one for weekday off-peak hours (remaining hours in day), and one for weekends. The response variable in all models is a binary variable denoting the occurrence of either a KABC or KABCO crash, depending on the model. We use a mixed effect logistic regression model to correlate the odds of crash occurrence with the variables listed in Table 16. The mixed effect model was used to account for repeated observations for each segment over time. For example, for morning peak hour models, the model includes 4 hours times 4 years equals 16 records for each segment. The mixed effect model can account for any location heterogeneity over time. Let us assume that $\mathrm{y_{is}}$ denotes crash occurrence on segment "s" during the i-th hour of the day each year (either 1 if a crash occurred or zero if no crash is observed). Likewise, let us assume P_{is} denotes the probability of crash occurrence on segment "s" during the same time of the day. Then, the mixed effect logistic regression model can be written as described in Eq. (1):

$$\mathrm{y_{is}} \sim \mathrm{Bernoulli}(\mathrm{P_{is}}) \equiv \mathrm{P_{is}}^{\mathrm{y_{is}}}(1-\mathrm{P_{is}})^{(1-\mathrm{y_{is}})} \tag{1-a}$$

$$\mathrm{Logit}\ (\mathrm{P_{is}}) = \mathrm{Ln}\left(\frac{\mathrm{P_{is}}}{1-\mathrm{P_{is}}}\right) = \beta_0 + \sum_{\mathrm{j}=1}^{M}(\beta_\mathrm{j} \mathrm{X_{j,is}}) + \varepsilon_\mathrm{s} \tag{1-b}$$

where,

β_0: common intercept (constant).

β_j: Coefficient on j-th variable

$\mathrm{X_{j,is}}$: the value of the j-th time-dependent variable for the segment "s", during the i-th time of the day [note: some variables, such as geometric characteristics, are not time dependent].

M: Number of independent variables.

ε_s: The random effect component for segment "s".

5.3. Modelling Results

This section presents the modeling results for urban and rural limited access highways. The dataset was analyzed for correlations, and it was determined that speed limit and average hourly speed were correlated. Models were estimated with speed limit or average speed as variables. Including average speed improved the statistical fit of models better than including speed limit. Therefore, the average hourly speed was used in the models. Models were estimated for all crashes (fatal [K], incapacitating injury [A], minor injury [B], possible injury [C], and property damage only [O]) and for only fatal and injury crashes (K, A, B, and C crashes) for both urban and rural roadway segments. The observations were divided into four datasets for weekday morning peak, weekday evening peak, weekday off-peak, and weekends. Coefficients are reported for all variables that were significant at the 95% confidence level (unless otherwise stated). The odds ratios are only reported for dummy variables. The AIC and BIC criteria were used to select the best model. The AIC and BIC values for final models are shown in Tables 17-20.

5.3.1. Models for Urban KABCO Crashes

Table 17 shows the modelling results for total (KABCO) crashes on urban limited access highways in Maine. The results show that there is a positive association between the traffic volume and crash occurrence, with a larger coefficient during weekday peak hours. When the coefficient on log of the volume variable is less than one, the crash risk curve is steeper at lower volumes whereas when the coefficient is greater than one, the crash risk curve is steeper at higher volumes. The modeling results show that the shape of the crash risk curve changes by time of day. During the weekday morning, and off-peak hours, the coefficient is less than one, indicating that the crash risk increases at a lower rate as volume increases. However, during the weekday evening peak hours, and weekends, this coefficient is greater than one, indicating that the crash risk increases at a higher rate as volume increases.

Table 17: Modelling Results for KABCO Crashes on Urban Roadways.

Category	Variables	Weekdays						Weekends	
		Morning Peak		Evening Peak		Off Peak			
		Mean (S.E.)[1]	Odds Ratio[4]	Mean (S.E.)[1]	Odds Ratio[4]	Mean (S.E.)[1]	Odds Ratio[4]	Mean (S.E.)[1]	Odds Ratio[4]
Intercept	**Intercept**	-14.5 (1.45)	-	-14.7 (1.83)	-	-10.6 (0.874)	-	-14.7 (0.600)	-
Exposure	**log (Avg. Volume)**	1.30 (0.187)	-	1.51 (0.172)	-	0.840 (0.107)	-	1.24 (0.074)	-
Operational Speed	**Avg. Hourly Speed**	insig[2]	-	-0.037 (.016)	-	insig[2]	-	insig[2]	-
	CV of Hourly Speed	18.98 (3.53)	-	29.3 (3.50)	-	9.25 (3.43)	-	26.9 (1.73)	-
Year	**Year 2021**	insig[2]	-	0.544 (0.168)	1.65	0.232[3] (0.136)	1.26	0.274 (0.093)	1.32
	Year2022	insig[2]	-	0.437 (0.200)	1.43	insig[2]	-	0.259 (0.094)	1.30
Roadway Geometry	**Curve Presence**	insig[2]	-	insig[2]	-	insig[2]	-	insig[2]	-
	More Than 2 Lanes	-0.972 (0.286)	0.38	-0.971 (0.278)	0.38	-0.578 (0.245)	0.56	insig[2]	-
Goodness-of-Fit Metrics	**AIC**	1686		2221		2194		6161	
	BIC	1717		2271		2234		6206	
	Log Likelihood	-834		-1102		-1091		-3074	

[1]Standard Errors.
[2]Insignificant variable.
[3]Significant at 90% confidence level.
[4]Odds ratios only reported for dummy variables.

Two speed variables were incorporated in the models, average hourly speed, and CV of average hourly speed. Average hourly speed is insignificant, in most cases, except in evening peak hours. During evening peak hours, there is a significant negative relationship between the hourly average speed and the crash occurrence. The coefficient of variation of average hourly speed is significant in all the models. Because the coefficient of variation is calculated by dividing the standard deviation of average hourly speed by the mean, the value of the coefficient of variation is very small, as can be seen in Table 1. Consequently, the model produces very large coefficients for the CV variable. The models indicate that the impact of CV of hourly speed is greatest during peak hours, specifically evening peak hours, and is the least during off-peak hours.

To explain how the odds of crash occurrence has changed in the years following the COVID-19 restrictions, two dummy variables were included: one signifying the year 2021 and the other the year 2022. The coefficient of the 2021 dummy is positive and significant during the weekday evening peak and off-peak hours as well as weekend hours. The odds of crash occurrence increases by 65% and 26% respectively during the weekday evening peak and off-peak hours and by 32% during the weekend hours compared to pre-pandemic years (2018-19). During 2022, the odds of a crash increase by 43% during weekday evening peak hours and 30% during weekend hours compared to the pre-restriction period.

Additionally, if the highway has more than two lanes (in the same direction), the odds of a crash occurrence is reduced by 62.2%, 62.1%, and 44%, respectively, for weekday morning peak hours, evening peak hours, and off-peak hours. This indicates that with more lanes on a roadway, the chances of a crash happening are reduced. The other geometric characteristics of roadway segments included in the model did not have significant effects on the odds of a crash.

5.3.2. Models for Urban KABC crashes

Table 18 shows the modelling results for the urban limited access highways with KABC crashes as the response variable. Like the KABCO models, the natural log of average hourly volume is again positively associated with an increased odds of crash occurrence. During the weekday morning, and off-peak hours, and weekends, the coefficient on log of volume is less than one, meaning that the crash risk increases at a lower rate as volume increases. However, during the weekday evening peak hours, this coefficient is greater than one, indicating that the crash risk increases at a higher rate as volume increases. There is a 52.9% reduction in the odds of crash occurrence during evening peak hours if the roadway has more than two lanes (compared to two lanes). The number of lanes is not significant during other time periods. Other geometric characteristics of the roadway are also not significant in the models.

Table 18: Modelling Results for KABC Crashes on Urban Roadways.

Category	Variables	Weekdays						Weekends	
		Morning Peak		Evening Peak		Off Peak			
		Mean (S.E.)[1]	Odds Ratio[4]	Mean (S.E.)[1]	Odds Ratio[4]	Mean (S.E.)[1]	Odds Ratio[4]	Mean (S.E.)[1]	Odds Ratio[4]
Intercept	**Intercept**	-10.1 (2.26)	-	-14.6 (1.96)	-	-12.9 (1.53)	-	-12.7 (0.915)	-
Exposure	**log (Avg. Volume)**	0.588 (0.287)	-	1.11 (0.242)	-	0.879 (.186)	-	0.907 (0.118)	-
Operational Speed	**Avg. Hourly Speed**	insig[2]	-	insig[2]	-	insig[2]	-	insig[2]	-
	CV of Hourly Speed	13.4 (5.76)	-	20.7 (3.53)	-	15.7 (5.45)	-	17.3 (2.35)	-
Year	**Year 2021**	-1.30 (0.413)	0.27	0.624 (0.229)	1.87	0.580 (0.234)	1.79	insig[2]	-
	Year2022	insig[2]	-	insig[2]	-	insig[2]	-	insig[2]	-
Roadway Geometry	**Curve Presence**	insig[2]	-	insig[2]	-	insig[2]	-	insig[2]	-
	More Than 2 Lanes	insig[2]	-	-0.752 (.374)	0.47	insig[2]	-	insig[2]	-
Goodness-of-Fit Metrics	**AIC**	774		1010		864		2651	
	BIC	805		1047		897		2681	
	Log Likelihood	-382		-499		-427		-1321	

[1]Standard Errors
[2]Insignificant variable.
[3]Significant at 90% confidence level.
[4]Odds ratios only reported for dummy variables.

Average hourly speed is insignificant in all models; on the other hand, the CV of hourly speed is a significant variable in all situations. The association between the CV and crash occurrence is positive, with its largest coefficient during weekday evening peak hours. The dummy variable denoting the year 2021 is significant for all weekday models. For weekday morning peak, evening peak, and off-peak hours, respectively, the odds of a crash in 2021 decreases by 73.8% and increases by 87% and 79%. The negative sign of the dummy variable for the year 2021 during the weekday morning. The decrease in odds in 2021 for weekday morning peak hours is presumably due to some morning travelers shifting to the off-peak hours in 2021, which results in fewer crashes in 2021 during weekday morning peak but more during the weekday off-peak hours. For weekends, there is no significant change in KABC crashes in 2021 or 2022. These trends are further discussed in Section 5.

5.3.3. Models for Rural KABCO crashes

Table 19 shows the modeling results for the rural total (KABCO) crashes. Like what was observed on urban roadways, there is a positive and significant relationship between the average hourly volume and crash occurrence. The relationship between the volume and crash risk is like what was observed for urban roads. For weekday morning, and off-peak hours, crash risk increases at a lower rate as volume increases, whereas for weekday evening peak hours and weekends at a higher rate as volume increases. Average hourly speed is insignificant for weekdays and is slightly negatively associated with weekend crash occurrences. The coefficient of the CV of hourly speed is significant and positive. The coefficients indicate the strongest impact of speed to be during the morning and evening peak hours, with the lowest impact during the off-peak hours. Out of all the models, the only significant geometric variable was the number of lanes during evening peak hours. This was found to coincide with a 47.1% reduction in the odds of a crash during evening peak hours on roadways with more than two lanes in the same direction.

Table 19: Modelling Results for KABCO Crashes on Rural Roadways.

Category	Variables	Weekdays						Weekend	
		Morning Peak		Evening Peak		Off Peak			
		Mean (S.E.)[1]	Odds Ratio[4]	Mean (S.E.)[1]	Odds Ratio[4]	Mean (S.E.)[1]	Odds Ratio[4]	Mean (S.E.)[1]	Odds Ratio[4]
Intercept	**Intercept**	-14.4 (1.52)	-	-13.9 (1.31)	-	-9.72 (.648)	-	-8.99 (1.26)	-
Exposure	**log (Avg. Volume)**	1.17 (.199)	-	1.18 (.173)	-	.681 (.087)	-	.859 (.068)	-
Operational Speed	**Avg. Hourly Speed**	insig[2]	-	insig[2]	-	insig[2]	-	-.031[3] (.018)	-
	CV of Hourly Speed	28.7 (4.24)	-	18.3 (3.08)	-	7.62 (2.48)	-	12.8 (1.82)	-
Year	**Year 2021**	insig[2]	-	insig[2]	-	insig[2]	-	0.035 (.101)	1.04
	Year2022	.383 (.155)	1.46	.305 (.138)	1.36	insig[2]	-	0.348 (.104)	1.42
Roadway Geometry	**Curve Presence**	insig[2]	-	insig[2]	-	insig[2]	-	insig[2]	-
	More Than 2 Lanes	insig[2]	-	-.637 (.271)	0.53	insig[2]	-	insig[2]	-
Goodness-of-Fit Metrics	**AIC**	2039		2231		2944		7720	
	BIC	2070		2268		2971		7273	
	Log Likelihood	-1014		-1109		-1468		-3606	

[1]Standard Errors.
[2]Insignificant variable.
[3]Significant at 90% confidence level.
[4]Odds ratios only reported for dummy variables.

The dummy variable for 2021 is only significant for weekends, with a 4% in the odds of a crash. For 2022, the odds of a crash increases by 46% during morning peak hours and by 36% during evening peak hours compared to the pre-restriction period (2018-19). During weekends, the odds of a crash increases by 42% as compared to the pre-restriction period. During off-peak hours, the dummy variable denoting the year is not significant.

5.3.4. Models for Rural KABC Crashes

The modeling results for rural KABC crashes are shown in Table 20. Like previous models, when significant, the average hourly volume is positively associated with the crash occurrence. The average hourly speed is insignificant for all models. However, the variation of speed (as reflected in CV of hourly speed) is a significant variable for all models except for morning peak hours. The CV of hourly speed has the strongest positive relationship with crash occurrence during the weekend hours. Geometric characteristics were also all insignificant.

Table 20: Modelling Results for KABC Crashes on Rural Roadways.

Category	Variables	Morning Peak		Evening Peak		Off Peak		Weekend	
		Mean (S.E.)[1]	Odds Ratio[4]	Mean (S.E.)[1]	Odds Ratio[4]	Mean (S.E.)[1]	Odds Ratio[4]	Mean (S.E.)[1]	Odds Ratio[4]
Intercept	Intercept	-6.33 (.260)	-	-11.3 (2.02)	-	-9.23 (1.002)	-	-6.12 (.189)	-
Exposure	log (Avg. Volume)	Insig[2]	-	0.628 (0.262)	-	0.358 (0.133)	-	Insig[2]	-
Operational Speed	Avg. Hourly Speed	Insig[2]	-	Insig[2]	-	Insig[2]	-	Insig[2]	-
	CV of Hourly Speed	Insig[2]	-	8.36[3] (4.61)	-	8.43 (4.06)	-	9.32 (2.34)	-
Year	Year 2021	Insig[2]	-	Insig[2]	-	Insig[2]	-	-0.229[3] (0.125)	0.80
	Year 2022	Insig[2]	-	Insig[2]	-	Insig[2]	-	Insig[2]	-
Roadway Geometry	Curve Presence	Insig[2]	-	Insig[2]	-	Insig[2]	-	Insig[2]	-
	Narrow Shoulder	Insig[2]	-	Insig[2]	-	Insig[2]	-	Insig[2]	-
	More Than 2 Lanes	Insig[2]	-	Insig[2]	-	Insig[2]	-	Insig[2]	-
Goodness-of-Fit Metrics	AIC	1015		1163		1358		3460	
	BIC	1027		1188		1385		3490	
	Log Likelihood	-505		-577		-675		-1726	

[1]Standard Errors
[2]Insignificant variable.
[3]Significant at 90% confidence level
[4]Odds ratios only reported for dummy variables.

The dummy variables signifying the years 2021 and 2022 are insignificant in almost all cases except for the weekend hours in 2021. During the weekend hours in 2021, the odds of a crash occurrence is reduced by 20.5%. It is worth pointing out that the crash counts in datasets used to estimate these rural models are smaller, which makes it harder to identify associations. This particularly showed in the model estimated for weekday morning peak hours in which all variables became insignificant. In addition, there is likely to be less commuting on rural highways than urban highways, so perhaps the pandemic effect is less pronounced for non-commuting traffic.

5.4. Summary and Conclusions

Traffic operation has strongly been affected since the start of pandemic, and this has impacted traffic safety. In particular, the rate of crashes (especially fatal/injury crashes) increased. In Maine, the results in the previous chapter demonstrated a significant increase in speeding behavior of drivers since the start of the pandemic. The models developed in this chapter aimed to explain the relationship between operational speed and crash occurrence and explore the trend of crashes and determine if factors other than the operational speed also contributed to the crash increase in the years after onset of the pandemic. The crash occurrence was analyzed using a short duration logistic regression model for both urban and rural roadways, and for both KABCO (total) and KABC (Fatal-Injury) crashes on limited access highways in Maine. The models were developed for different times of the week to better understand crash occurrence trends.

One interesting trend is a reduction in the odds of KABC crashes during weekday morning peak hours and an increase in weekday evening and off-peak hours in 2021. Explanatory analysis conducted early in this study showed that during the travel restriction period there was a shift in volumes during the morning peak, with its prominence being reduced. Trips that had been taken during the morning peak period have been redistributed to other parts of the day. As such, this is the effect that is likely being captured by these changes in odds of crash occurrence. As morning commuting is not as necessary with the ability to work from home, the morning volume has reduced. Consequently, the odds of a crash occurrence is reduced during the weekday morning period. A similar trend (with potentially same reason) was observed in KABCO models on the urban limited access highways, except that in these models, the only significant effects were during the weekday evening and off-peak hours - increases in the odds of speeding of 65% and 26% respectively. The dummy variable signifying the year 2022 is often either insignificant or has a smaller coefficient than that of 2021 when significant. This effect presumably corresponds with traffic operations returning to pre-restriction conditions. However, the odds of crash occurrence are still higher compared to pre-pandemic.

The average hourly speed was largely insignificant throughout all the models. The only cases of significance were for the urban weekday evening KABCO and rural weekend KABCO models. In both cases it bore a small and negative coefficient, indicating slight reductions in crash odds with increased speeds. This is an unexpected result, as vehicle speed has been found to be directly associated with a crash occurrence or severity (Abegaz et al., 2014; Adanu, Agyemang, et al., 2021; Cooper, 1997). As discussed by Park et al. (2021), the effect of average speed is challenging to be captured in crash models. Many variables affect crash occurrence, and their effects cannot always be captured in data collection. This makes relationships between predictors and response variables hard to identify. One potential cause for the variable being largely insignificant, or negative, is that higher speed roadways are built to a higher standard. This could mean that geometric variables which were unavailable, such as curve radius, grade, or sight distance, have an effect at higher speeds that is not being accounted for in the model. Another potential explanation is that average hourly speed was largely insignificant because the variability of average hourly speed was a more impactful variable.

The coefficient-of-variation of hourly speed is positively associated with crash occurrence. This is a sensible relation, as variability of the average hourly speed affects the upper limit of driver's speed choice. As such, this variable tells us that when the average hourly speed is higher, there is a greater chance of a crash. Likewise, when the average hourly speed is lower there is a lesser likelihood. This variable can in part be used to explain the negative relationship and insignificance of average hourly speed with regards to crashes. These two variables tell us that crash occurrence is not so much related to the actual average hourly speed, as opposed to its variation. For example, as illustrated by Figures 3-8, hours with greater standard deviations in speed will have more drivers travelling faster for a given mean speed. Even though standard deviation of hourly speed reduced for some speed limits and times of day, as seen in Table 14, the exponential relationship between crashes and speed means that any variability, if at a higher average speed, will still lead to an increase in the chance of a crash. The changing ratio between standard deviation and average is captured by the CV, allowing the effect to be clearly measured.

This chapter aimed to demonstrate the long-term effects of the COVID-19 travel restrictions. Using data from before and after the restrictions (2018-19 and 2021-22), models were estimated to understand the long-term effects of COVID-19 pandemic on crash occurrence. This chapter also contributes to existing literature by demonstrating the use of probe data to perform network-level analyses to build a relationship between crash occurrence and speed information. Using probe data, we were able to collect hourly volume and speed information to estimate the average volume, average hourly speed, and CV of hourly speed on each segment and use that in models. The analysis of data from 2022 also provides insights into emerging conditions, which have been studied by very few (if any) papers previously. Furthermore, this study looks at the influence of speed on the crash occurrence following the pandemic. The models largely find that average speed is not explaining the occurrence of crashes; however, variability in speed is. This can help transportation safety practitioners by highlighting a reduction in speed variability as a strategy to improve safety and reduce crashes. One major limitation was the data for 2018. The quality of this data was lower than that of subsequent years, showing that while probe data is a good tool, because the technology is new there is not extensive historic data. Future research could investigate the application of other probe data sources to model the crash occurrence.

Chapter 6: Recommendations and Future Research

Maintaining system operational efficiency of transportation infrastructure, including both traffic flow and safety, is becoming more and more of concern in the face of diminishing funds available to transportation agencies for construction and maintenance. Recent history suggests that system operational efficiency is increasingly challenged by unexpected disruptions in traffic demand caused by natural disasters and other emergencies, such as the COVID-19 pandemic. Transportation agencies will need to be prepared for the safety and operational impacts of such disruptions in traffic volume as they manage system operational efficiency. This study found that in addition to drastic reduction in traffic volume, other factors (presumably, reduction in speeding enforcement or change in perceived risk) also influenced the increase in operational speed (or speeding, to be exact) during the comprehensive stay-at-home order. The modeling results show that the odds of speeding increases during times with drastic reduction in traffic volume, such as the pandemic. These results could be used to guide agencies in deploying enforcement resources to minimize speeding should these circumstances arise again.

This study showed that speeding increased significantly across different urban and rural facility types in New England since the COVID-19 pandemic, especially during peak hours. Although the odds of speeding in 2021 is relatively smaller than in 2020, still, it is substantially above the pre-pandemic level. These results show that the massive disruption in travel demand, or traffic volume, can have a profound impact on the operational speed or speeding that can have lasting effects long after the disruption has ceased. Roadway operating agencies should consider this likelihood of increases in drivers speeding whenever unexpected reductions in travel demand or traffic volume occur, and properly plan for such incidents where possible to reduce the expected increases in fatal crashes.

Speeding is a major factor in fatal and serious injury crashes; recognizing that speeding has substantially increased, in both Maine and Connecticut, compared to pre-pandemic conditions suggests the need for exploring countermeasures or interventions to decrease speeding and raise public awareness, to enhance roadway safety. Understanding how enforcement changed after pandemic is also essential to reduce speed on roadways, or develop intervention programs, and countermeasures. Given the models' considerations of roadway characteristics and temporal variables, the conditions, and times that the odds of speeding are greater can be identified. This allows for speeding countermeasures to be targeted accordingly, to make the most of potentially limited resources.

Furthermore, this study looked at the influence of speed on crash occurrence following the pandemic and if any other factor other than speed impacted the change in crash occurrence trend in 2021 and 2022. The models largely find that average speed is not explaining the occurrence of crashes; however, variability in speed is. This can help transportation safety practitioners by highlighting a reduction in speed variability as a strategy to improve safety and reduce crashes. Finally, with departments of transportation having limited budgets, the push to both increase roadway operational efficiency and safety together can pose a burden. The establishment of a link between the odds of speeding and the level of service achieved by a roadway can be helpful to these agencies in simultaneously designing capacity and safety improvements for roadways.

Although limited access roads have higher design standards compared to other facility types, they experience a significant number of severe and fatal crashes due to higher volume and speed on these roads. The higher rates of severe crashes as well as the availability and greater accuracy of probe data sources on these roads were the two primary reasons that we focused on these roads in this study. In addition, given that the level of service on freeways depends on traffic density, we were able to establish a link between level of service on these roads and odds of speeding using probe data. Future research is recommended to explore the odds of speeding on other roadway facility types using probe data. Future studies could also examine how COVID-19 case rates, death rates, or how factors like unemployment or population density affect the odds of speeding and how higher speeds impact roadway safety. From methodological perspective, in this study, we used binomial and logistic regression models, due to their flexibility to model binary response variables, and interpreted the results using the change in odds of speeding. Other methods such as time series models (e.g., multivariate timeseries) can also be used and are suggested for future studies. with different population or density.

The COVID-19 pandemic has given the world numerous unprecedented challenges, and the transportation sector has been no exception. As transportation evolves, so do the problems and obstacles related to transportation safety. Even as this report is written, the safety effects from the pandemic remain relevant. Studies around the world, including this report, indicate that upon the reduction in traffic volume, due to travel restrictions, the rates of severe and fatal crashes increased. Unlike this study, however, most studies examining roadway safety were explanatory in nature and did not involve statistical models to determine detailed contributing factors. These models can be used to better understand and mitigate the contributing factors and their outcomes. Furthermore, most crash analyses and evaluations only compared the pre-pandemic time periods to some or all of 2020, especially right after the pandemic started (March-June 2020). Only a few studies continued the analysis into 2021 and 2022 (as we did in this study). As noted earlier, NHTSA data (2022) indicated that crash rates were still elevated in the U.S. in 2022, compared to 2019. Therefore, it is necessary to explore how roadway safety was impacted in 2022 and later. This opens the door to plenty of future research to develop statistical models or examine interventions and countermeasures to limit risky behaviors or decrease crashes. For example, some studies found that there was an increase in the number of DUI crashes; however, no recent study aimed to quantify the impact of intoxicated driving on severe-injury and fatal crashes or how to reduce DUI cases. Finally, of the studies identified in this literature review, many of them were focused on the U.S. or Canada, with several more coming from Europe, the Middle East, and Asia. This could represent a large research gap in several regions. Little roadway or pedestrian safety information came out of Northern Europe, Australia, Africa, or South America. These would be relevant to the body of research produced as these regions represent different approaches to transportation, COVID-19 response, and social attitude.

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